“Essays in Search and Matching in Labor Markets”

TESIS PARA OPTAR AL GRADO DE DOCTOR EN ECONOMÍA

Alumno: José Pablo Valenzuela Álvarez

Profesor Guía: Esteban Puentes

Profesores Co-guía: David Coble, Benjamín Villena

Este trabajo ha sido parcialmente financiado por CONICYT, mediante beca de doctorado nacional, folio: 21191751

Santiago, Julio 2023

To my beloved Dani, our dog Osito, my parents, my brother, and Lela...

Agradecimientos

Quiero agradecer profundamente a mis guías de tesis: Benjamín Villena, David Coble y Esteban Puentes, por su dedicación, paciencia, disponibilidad, prolijidad, y asertividad al momento de que se presentaran dudas. Valoro enormemente sus esfuerzos por ayudarme a ejecutar mis proyectos de investigación en cada etapa del proceso, y a aplicar el máximo rigor en todo momento. Aprendí mucho de ustedes. Destaco que, además de los aspectos técnicos, puedo decir que son grandes personas; cada vez que llegué con alguna duda o inquietud sobre el futuro en la profesión, o el advenimiento de alguna decisión importante, siempre se tomaron el tiempo para darme buenos consejos y orientarme de la mejor manera posible. Espero poder replicar todo lo que aprendí de ustedes, tanto en lo personal como en lo profesional.

Estoy, además, infinitamente agradecido de Nicolás Riquelme, un gran colega, mentor y amigo que conocí durante el proceso por casualidades de la vida. Muchas gracias, Nico, por tu entusiasmo y curiosidad al momento de hablar de investigación, como también por tu muy buena voluntad para ayudarme y orientarme durante las distintas etapas del ciclo del doctorado. Largas conversaciones -tanto de la vida como de economía- cimentaron el camino a la colaboración profesional y a una gran amistad.

Agradezco, también, a *La Cueva*: Vicente Corral, Martín Dibarrart, Ignacio Rojas, Martín Ferrari, Brian Castro, Patricio de Araya y Nicolás Rojas. Largas -infinitas- sesiones de estudio en La Cueva forjaron una linda amistad que se mantiene hasta el día de hoy. Sin ustedes el proceso no hubiese sido lo mismo. Fueron el alivio cómico en los tramos complicados de la película.

A mi familia. Gracias a mi padre por ser incansable en su intención de mostrarme que el cariño y pasión por lo que haces, a la larga, rinde frutos. Gracias por tu paciencia y por confiar en mi, a pesar de que muchas veces el panorama se vió con tintes grises. Tambien te agradezco por ser mi *partner* del tenis, mi amado deporte. Gracias a mi madre por enseñarme el idioma inglés desde muy pequeño; me ha sido de enorme utilidad para mi profesión, y para la vida. Por sobretodo, gracias por tu infinita buena voluntad y preocupación; gracias por siempre decir *sí* cuando te necesité. Gracias a mi hermano, Diego, por ser mi gran amigo, *partner* de conversaciones, videojuegos, y de la vida. Gracias por inspirarme a que se puede soñar en grande. Gracias a mi abuela, *Lela*, por ser el mejor ejemplo para sus nietos, por el cariño que irradia a la familia, por la infinita paciencia y templanza, y por mostrarme el amor a la docencia (a ti también, mamá) y a seguir aprendiendo, sin importar la edad.

Finalmente, gracias a mi mujer, Daniela. Gracias por acompañarme en este largo camino, siempre con la mejor disposición, cariño y energía. Gracias por ser mi principal soporte emocional, especialmente cuando las cosas se pusieron complejas. Gracias por quererme y respetarme por lo que soy. Gracias por empujarme a ser mejor persona. Admiro tu capacidad de resistencia a la adversidad y amor al trabajo. Gracias por hacerme reir. Gracias por compartir esto, y tantas otras cosas conmigo. Gracias por compartir tus días conmigo. Gracias por el camino recorrido.

Acknowledgments

I want to deeply thank my advisors: Benjamín Villena, David Coble and Esteban Puentes, for their dedication, patience, availability, prolixity, and assertiveness when doubts arose. I greatly appreciate your efforts in helping me execute my research projects at every stage of the process, and in applying the utmost rigor at all times. I learned a lot from you. I emphasize that, in addition to the technical aspects, I can say that they are great people; every time I came in with some doubt or concern about the future in the profession, or the advent of some important decision, they always took the time to give me good advice and guide me in the best possible way. I look forward to replicating everything I learned from you, both personally and professionally.

I am also infinitely grateful to Nicolás Riquelme, a great colleague, mentor and friend that I met during the process by chance. Thank you very much, Nico, for your enthusiasm and curiosity when talking about research, as well as for your great willingness to help and guide me during the different stages of the Ph.D cycle. Long conversations -both about life and economics- paved the way for professional collaboration and a great friendship.

I also thank *La Cueva*: Vicente Corral, Martín Dibarrart, Ignacio Rojas, Martín Ferrari, Brian Castro, Patricio de Araya and Nicolás Rojas. Long -infinite- study sessions at La Cueva forged a beautiful friendship that remains to this day. Without you the process would not have been the same. You were the comic relief in the difficult stretches of the film.

To my family. Thanks to my father for being tireless in his intention to show me that the love and passion for what you do, in the long run, pays off. Thank you for your patience and for trusting me, despite the fact that many times the outlook was seen with shades of gray. I also thank you for being my partner in tennis, my beloved sport. Thanks to my mother for teaching me the English language from a very young age; it has been of enormous use to me for my profession, and for life. Above all, thank you for your infinite goodwill and concern; thank you for always saying *yes* when I needed you. Thanks to my brother, Diego, for being my great friend, partner in conversations, video games, and in life. Thank you for inspiring me to dream big. Thanks to my grandmother, *Lela*, for being the best example for her grandchildren, for the love she radiates to the family, for her infinite patience and temperance, and for showing me her love for teaching (to you too, mom) and to continue learning, regardless of age.

Finally, thanks to my wife, Daniela. Thank you for accompanying me on this long road, always with the best disposition, affection and energy. Thank you for being my main emotional support, especially when things got complex. Thank you for loving me and respecting me for who I am. Thank you for pushing me to be a better person. I admire your ability to resist adversity and love of work. Thank you for make me laugh. Thank you for sharing this, and so many other things with me. Thank you for sharing your days with me. Thanks for the journey.

Contents

Introduction

This thesis studies the relevance of labour market frictions through two different research questions. The goal is to highlight that this kind of frictions may explain some phenomena which may seem quite counterintuitive at first sight but, when looking into the detail, labour market frictions provide us reasonable explanations to the events that we observe in workers' dynamics.

Chapter 1 studies that -in *job-to-job* (JTJ) transitions- wage cuts are often associated with lower continuation values for workers when comparing the new job with the former one. However, when considering a job offer workers may trade-off other non-monetary features of the offer that compensate current wage losses. In this paper, I study which is the trade-off that workers face when accepting a wage cut. Using data from the Chilean Unemployment Insurance registry, I show that *job-to-job* transitions are positively associated with ex-post wage growth. Besides, conditional on a JTJ transition, workers who accept wage cuts show higher wage growth rates in their destination firms. These facts are robust to changing the composition of jobs and workers over the business cycle.

In Chapter 2, using data for the Chilean mining sector, we provide SVAR evidence in order to answer the research question regarding what 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). We 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, we 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, we 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.

The contribution of this thesis is twofold. First, it shows robust evidence regarding that workers face a trade-off between current wages and future wage growth rates when facing a job offer. This may have several policy implications regarding, for example, unemployment insurance or pension savings policy. Second, this thesis provides novel evidence in a commodity sector for a developing country- regarding that commodity price shocks may affect in different directions both the employment and wage gaps for workers with different levels of education. In this regard, it also offers a structural model in which labour market frictions explain this novel phenomena observed in the data.

Chapter 1

Job-to-Job Transitions: Wage Cuts and Wage Growth. Evidence for a Developing Economy

1.1 Introduction

Standard on-the-job search theory predicts that movers will enjoy higher utility continuation values in their new positions, which may come from wage improvements when arriving at a new job. In this sense, Jinkins and Morin (2017)[31] document that job-to-job (JTJ) mobility is associated with an average real wage gain of two percent, which is about twenty times higher than the average real wage gain experienced by workers who stay in their current job in a typical year. This fact is also documented by others, such as Topel and Ward (1992)[45] and Eckstein et al. (2011)[20]. While there is evidence supporting average wage gains associated to JTJ transitions, some papers show that JTJ transitions hide a substantial share of wage cuts. In this regard, there is a body of work that documents this issue in different environments and labor markets (Connolly and Gottschalk (2008)[15]; Tjaden and Wellschmied (2014)[44]; Albagli et al. (2018)[2]).

In light of the evidence of wage cuts associated with JTJ transitions, one may ask: What reasons do workers consider for taking a wage cut when doing a job transition? To the best of my knowledge, so far the literature has studied three principal reasons regarding why workers accept wage cuts when doing a JTJ transition: (i) avoiding layoffs (Lizama and Villena (2019)[35]; Moscarini and Postel-Vinay (2018)[38]); (ii) match quality improvement (Jinkins and Morin (2017)[31]; Caplin et.al. (2020)[12]); and (iii) investment in future wage growth (Connolly and Gottschalk (2008)[15]; Postel-Vinay and Robin (2002)[40]). In this paper, I assess the research question on which is the trade-off that workers face when accepting a wage cut in a JTJ transition providing evidence in line with reason (iii). Using administrative data from the Chilean Unemployment Insurance (UI) database, I document several empirical facts that characterize JTJ transitions and the relationship between wage cuts and ex-post wage growth for job movers. These facts strongly suggest that JTJ movers trade-off current wage for future wage growth rates[1].

First, I show some descriptive facts about JTJ transitions. In line with other studies on this topic, JTJ transitions are more frequent among workers with lower salaries. Also, 44% of JTJ transitions in the sample I use here involve a real wage cut, which is a similar value to the one found in Albagli et al. (2018)[2] (49%), and that confirms that wage cuts are quite common amongst JTJ transitions. Then, I look at evidence that relates JTJ transitions with ex-post wage growth, i.e., the wage growth rate that a job mover obtains in her destination firm. I compare the wage growth rates that workers who make a JTJ transition in period t (movers) experience with the wage growth rates that workers who stay at their current job in period t (stayers) obtain. Considering all JTJ transitions, movers and stayers exhibit similar wage growth rates. Nevertheless, when I look at JTJ transitions that involve wage cuts, it is quite notorious that movers experience higher wage growth rates than stayers.

With these results in hand, I provide econometric evidence that accounts for the descriptive facts mentioned above. Specifically, running fixed effects regressions at the worker-level, I show that: (i) JTJ transitions are positively correlated with ex-post wage growth rates; (ii) workers who accept a wage cut experience ex-post wage growth rates even higher; and (iii) there is a job ladder effect in taking wage cuts, that is, workers who earn higher wages in their origin firms have a higher probability of taking a wage cut when doing a JTJ transition.

The last part of the empirical section adds workers that make Unemployment-Employment transitions (UE flows) in order to compare their wage growth rates with the ones experienced by workers that perform JTJ transitions. This evidence shows that JTJ movers exhibit higher wage growth rates than workers who come from unemployment, and these differences are systematic and statistically significant.

The reminder of the paper is organized as follows. Section 2 presents a literature review of the research in JTJ transitions and their relationship with wage

[1] Of course, the reasons (i), (ii) and (iii) aforementioned above are not mutually exclusive. For example, a worker who accepted a wage cut in order to avoid a potential layoff may also enjoy higher wage growth rates in her new job. My data does not allow me to disentangle the importance of each reason on workers accepting wage cuts because I do not observe features like workers' layoff probability, or some indicator that I can use as a proxy of job match quality. Despite of the latter, the panel nature of the data allows me to study the relation between wage cuts and wage growth rates under several specifications and different definitions for ex-post wage growth. Overall, the relationship is robust to those different setups, providing strong evidence on the wage cut and future wage growth rates trade-off characterizing JTJ transitions. The fact that the wage cut channel is through a higher future wage growth rate is without prejudice to the fact that channels (i) and (ii) may also occur to some extent.

cuts. Section 3 documents several stylized facts regarding JTJ transitions, wage cuts, and ex-post wage growth. Finally, Section 4 concludes.

1.2 Literature Review on JTJ transitions and wage cuts

This paper is related to the literature that studies JTJ transitions and the possibility that they do not necessarily imply a wage gain. To the best of my knowledge, the literature lists three different reasons for the latter. The first is accepting a wage cut as a mechanism to *avoid layoffs*. In this regard, Lizama and Villena (2019)[35] propose an on-the-job search model that features a stochastic dismissal shock. When employed workers expect that they may be dismissed from their current jobs with high probability, they exert search effort in order to move JTJ and to avoid having an unemployment time span in which their consumption may be lowered compared to past periods. In that sense, it is reasonable to expect that a worker facing that scenario may accept a wage cut and prevent being unemployed. Also, Moscarini and Postel-Vinay (2020)[38] introduce the possibility that workers who lose their job can immediately contact a substitute job. As the worker receives this contact, his outside option is unemployment, and he will therefore take up the new job, whatever its pay. This is known as a *godfather shock*, in the sense that any offer that the dismissed worker receives will be unrejected since his outside option is too low.

The second motive for taking wage cuts is related to an *investment in future wage growth*. Connolly and Gottschalk (2004)[15] propose a model of job choice that allows agents to account for differences in wage growth as well as starting wages when choosing between jobs. They use this framework to estimate the parameters of the underlying wage offer distributions and the probability of involuntary terminations. They show that roughly one-third of transitions to *worse* jobs (based on their lower wages) are, in fact, transitions to *better* jobs (based on their expected future wages) and, conversely, about 15% of the transitions to jobs with higher wages are transitions to jobs with lower expected future wages. In this same vein, Postel-Vinay and Robin (2002)[40] propose a model with search frictions and on-the-job search in which the latter feature forces employers to grant their employees wage raises randomly over time, so that wages differ across identical employer-employee pairs. This allows the model to account for wage cuts as a method to achieve higher wage growth rates when the tenure profile in the new firm is expected to increase over a very long time span.

The third reason for employed workers to accept wage cuts when moving JTJ is *match quality improvements* and *non-wage amenities*. Regarding the former, Jinkins and Morin (2017)[31] show evidence supportive of the *Compensation Hy-*

pothesis, which states that workers who move from higher to lower paying firms are compensated by an improvement in their match quality. About non-wage amenities, Sorkin (2018)[43] develops a framework to measure compensating differentials that takes into account the difficulty of measuring non-wage characteristics and the possibility of utility dispersion in the labor market. He finds evidence that compensating differentials play a role in explaining the variance in earnings.

This paper adds to the literature with novel evidence on the trade-off between current wages and future wage growth using a large administrative record for Chile for a time span of 14 years. The empirical evidence confirms that job movers experience higher wage growth rates than their job stayers counterpart and, furthermore, those workers who accept a wage cut are those who experience the higher wage growth rates.

1.3 Stylized facts

1.3.1 Data and Variable Definitions

The main source of information is a 5% sample of matched employer-employee data from the Chilean UI registry, which is provided by the *Superintendencia de Pensiones*. By law, the unemployment fund administrator is required to collect, on a monthly basis, all contributions to the individual unemployment accounts (and solidarity fund) for each labor relationship. Hence, our data consider only formal workers, who account for nearly 70% of the labor force (Cruz and Rau, 2022 [16]). The UI database provides information on individual characteristics, such as age, education, gender, monthly wages, contract type, and the year and month that an individual has been employed. Besides, it provides information regarding the employer, such as the average and standard deviation of wages that the employer pays to his workers and the number of months that a firm has been active. One caveat of the UI registry is that it does not have information regarding hours worked, therefore, I use monthly wages for the whole analysis that I performed. Despite the latter, Cruz and Rau (2022)[16] argue that the incidence of part-time work in the formal sector is only 4% in Chile and, thus, it is likely that the effects of part-time work in my analysis will be very limited.

With the information described above, I build a monthly panel. I focus on individuals from 18 to 60 years of age, in order to avoid retirement issues[2]. The UI system started in October 2002 with new job contracts, so the UI data has become more representative over time. In this regard, I used observations starting in January 2007, so I can avoid the selection problem of using data from workers who entered to the system during the early years of the system. The sample covers until December 2019, so that the COVID-19 pandemic effects on labor market outcomes do not play any role in the analysis. Besides, I only

[2]The age of retirement in Chile for men is 65, and 60 for women.

consider workers who have an indefinite term contract in the analysis. This is because workers that have a fixed term contract show atypical wage growth patterns, e.g., quarterly growth rates higher than 25%, which is quite far from what the literature has found (near of a 5%). Applying these criteria yielded a monthly panel of 16,718,875 observations, corresponding to 324,763 workers.

Prior to moving forward with the empirical results I have to define relevant concepts and variables. First, I define a *JTJ transition* as a change in worker's i firm ID in contiguous months. That is, if in December of 2009 worker i was working at firm h and in January of 2010 this worker appears in the database as working at firm j, we say that worker i did a JTJ transition from firm h to firm j. If there is a gap between months in the data that implies a change of firm ID from month-to-month, I say that the worker went through an unemployment spell. Considering the same case of worker i, now let us suppose that instead of appearing at firm j in January of 2010, he now appears an that firm in March of 2010. In that case, we say that worker's i labor flow went from firm h to unemployment, and from unemployment to firm j. On the other hand, I define an Employment-Unemployment (EU) transition if there is a gap between months in the data that implies a change of firm ID from month-to-month. Under this definition, I register 105,287 JTJ transitions from a total of 284,517 transitions (JTJ+EU). The latter means that 37% of observed transitions are JTJ, and 63% are EU transitions.

The UI registry database presents a weak point: the researcher can not observe hourly wages but only monthly ones. The latter implies a complication in order to characterize wage growth rates and in defining a variable that accounts for wage cuts when workers move *job-to-job*. Given this, let t be the period in which worker i does a JTJ transition or a UE transition (if unemployed in $t-1$) to firm j, then I define the *ex-post wage growth* as:

$$\Delta log(w_{i,j,t+k}) = log(w_{i,j,t+k}) - log(w_{i,j,t+1}), \text{ for } k \in \{3, 6, 12\}. \tag{1.1}$$

Using $log(w_{i,j,t+1})$ as the reference wage allows me to avoid the issue of worker i working partially (not the full month) in firm j, which comes from the fact of not observing the monthly hours worked. Equation (1.1) is conditional in that worker i does not make any job transition between period $t+1$ and $t+k$.

In the same spirit as before, let t be the period in which worker i does a JTJ transition, then I say that worker i took a *wage cut* when moving JTJ from firm h to firm j if $wc_{i,t} = 1$, where:

$$wc_{i,t} = \begin{cases} 1, & \text{if } w_{i,h,t-2} \geq w_{i,j,t+1} \\ 0, & \text{if } w_{i,h,t-2} < w_{i,j,t+1}. \end{cases} \tag{1.2}$$

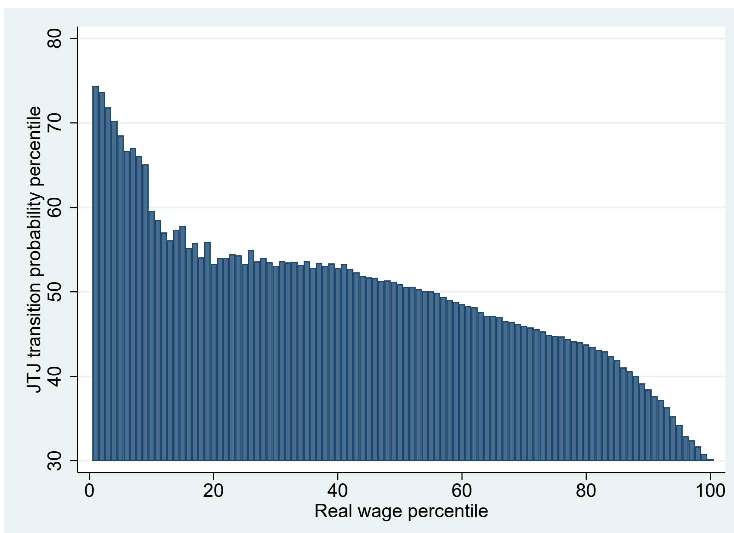
Here I assume that worker i works the full month in her origin firm in period $t-2$, and works the full month in her destination firm in period $t+1$. In other words, month $t-1$ is the last month a worker is reported attached to the old firm, and t is the first linked to a new firm. Hence, both months ($t-1$ and t) may have not been fully worked by the worker. Then, I take $t-2$ as the last complete month worked at firm h, and $t+1$ as the first complete month worked at firm j.

1.3.2 Evidence on JTJ transitions and wage cuts

First, I describe the distribution of the probability of a JTJ move by average real wage level. Here, for worker i, I define the probability of a JTJ move as the ratio between the total number of JTJ transitions in the time span that the worker i appears in the database, and the total number of periods that this worker is observed in the data. Specifically,

$$\mathbb{P}(JTJ) = \frac{\text{Total JTJ transitions}}{\text{Total periods in sample}}.$$

Figure 1.1: Average JTJ transition probability percentile by real wage percentile



Source: Author's calculations using the UI registry database.

That being said, Figure 1.1 shows the average JTJ transition probability percentile by real wage percentile. The relationship between transition probability and wages is clearly negative. Workers who earn low wages are those who have the highest job transition likelihood. This evidence is quite similar to what Albagli et al. (2018)[3][2]. Therefore, the fact that Figure 1 shows adds to the

[3]The exact plot that is shown in Albagli et al. (2018) displays the wage percentile profile by JTJ transition probability; that is, the axes are inverted in Figure 1 regarding their work.

evidence that there is a negative correlation between wages and JTJ transition probabilities that a worker does in her life cycle.

For the transitions described above, I describe the average JTJ real wage change in order to analyze how prevalent wage cuts are for these transitions. In this regard, despite the fact that the average real wage change from a JTJ transition is about 5.2%, Table 1 shows that 44.04% of the transitions imply a wage cut, which is, overall, consistent with the facts found in the literature (Connolly and Gottschalk (2008)[15]; Tjaden and Wellschmied (2014)[44]; Albagli et al. (2018)[2]).

Table 1.1: % of $job - to - job$ transitions that involve real wage cuts

	Absolute Frequence	Relative Frequence
$\Delta\ \log(w_t) > 0$	59,754	55.96
$\Delta\ \log(w_t) \leq 0$	47,029	44.04

Source: Author's calculations using the UI registry database.

The evidence in Table 1 raises the question on why the share of JTJ transitions involving a wage cut is so high if, in theory, a job transition should improve wage conditions for workers that make them. The UI database allows me to explore if there is a trade-off between accepting a lower wage level (i.e., taking a wage cut) and improving ex-post wage growth conditions. Thus, in the following sections, I will be providing some evidence on workers switching jobs and accepting wage cuts and the relation to their ex-post salary growth rates.

1.3.3 Movers v/s Stayers

The first exercise I perform is one of comparing the average real wage growth of job movers versus job stayers. Here, a *stayer* is defined as a worker who did not make a JTJ transition in period t. On the other hand, a *mover* is defined as a worker that made a JTJ transition in period t. Movers' wage growth is defined by equation (1.1) and, to avoid complications, stayers' wage growth is defined in similar fashion[4], with the difference that stayers are only observed

In order to present an appropriate comparison, Figure 24 in Appendix A displays the relation between JTJ transition probability and real wage using the same axis order as in Albagli et.al (2018).

[4] I performed all the analysis using alternative definitions for movers and stayers wage growth rates. For movers, I defined their wage growth rates as

$$\Delta log(w_{i,j,t+k}) = log(w_{i,j,t+k}) - log(w_{i,j,t+1}),\ \text{for}\ k \in \{4, 7, 13\}.$$

And for stayers, the alternative definition is

$$\Delta log(w_{i,h,t+k}) = log(w_{i,h,t+k}) - log(w_{i,h,t}),\ \text{for}\ k \in \{3, 6, 12\}.$$

The results in the paper do not qualitatively change with these alternative definitions.

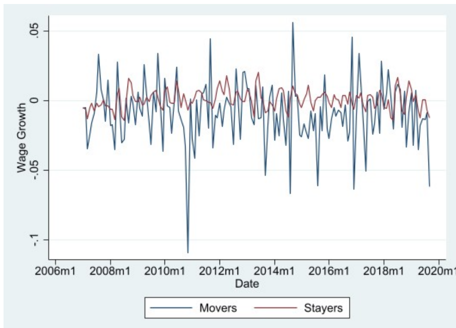
as matched in firm h, that is, in their origin firm. Specifically, stayers' wage growth is defined by

$$\Delta log(w_{i,h,t+k}) = log(w_{i,h,t+k}) - log(w_{i,h,t+1}), \text{ for } k \in \{3, 6, 12\}. \tag{1.3}$$

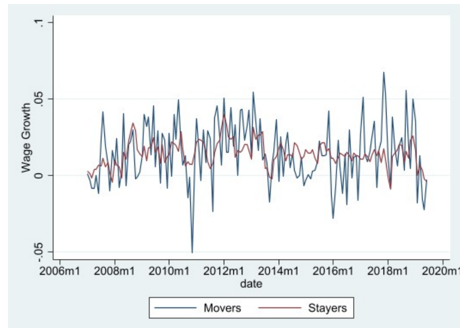
Figure 2 shows the average wage growth for movers and stayers from 2007:M1-2019:M12. Panel (a) displays the wage growth within a quarter; Panel (b) displays the wage growth within a semester; and Panel (c) shows the wage growth within a year. Movers exhibit average wage growth rates of -1%, 1.4% and 5.8%, respectively, while those for stayers are of 0.1%, 1.5% and 4.1%, respectively[5]. It can also be seen that as the time span goes longer, the wage growth rates increase, particularly for movers. What stands out from Figure 2 is that, on average, movers' salaries grow at a considerably greater rate after a year at the destination firm, compared to stayers'.
Another interesting fact can be seen in Figure 2. The three panels show that movers wage growth rates tend to decrease in recessions, such as the Global Financial Crisis of 2009. This fact is consistent with the evidence in Causa, Luu and Abendschein (2021)[13], and it may be attributed to the involuntary nature of separations and the *godfather shocks* proposed by Moscarini and Postel-Vinay (2020)[38].

[5] The reader will notice that wage growth rates for both, movers and stayers, exhibit a lot of noise in the sense that they fluctuate considerably month-to-month. This is due to the definition of movers and stayers stated above. That is, the fact that movers (and stayers) in period t are different to those in period $t+1$ yields that the sample for which I compute wage growth rates will change across different periods which, at the same time, has an impact in the average rates.

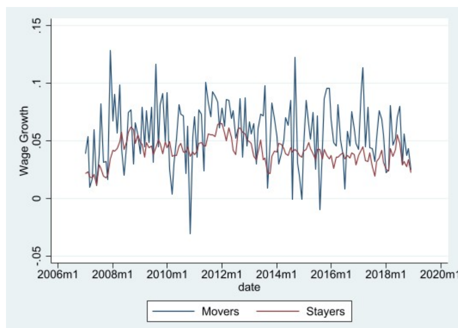
Figure 1.2: Movers v/s stayers average wage growth, 2007-2019



(a) Within a quarter



(b) Within a semester



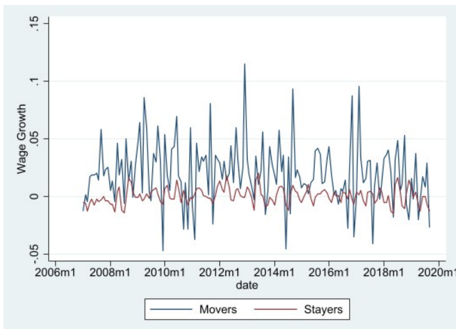
(c) Within a year

Source: Author' calculations using the UI registry database.

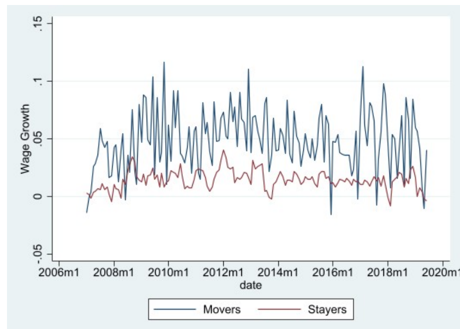
Figure 2 displays the average wage growth rates for the whole pool of movers. That is, the movers series displayed in Figure 2 considers movers who accept a wage cut and those who do not accept a wage cut. In Figure 3, I condition the wage growth rates for movers only for those who took a wage cut when doing a JTJ transition. This exercise might give a better look regarding whether there is, indeed, a trade-off between taking wage cuts and experiencing higher wage growth when workers switch to another job.

It is quite clear from Figure 3 that workers who accept a wage cut experience higher ex-post wage growth rates when compared with stayers. The latter is true for every horizon for which I calculate wage growth rates.

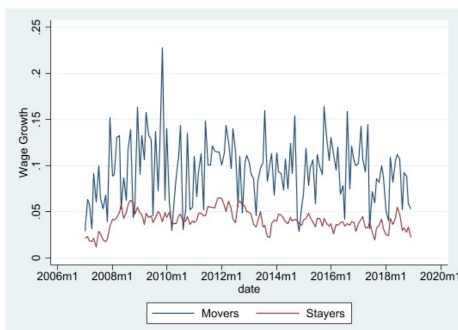
Figure 1.3: Movers v/s stayers average wage growth, 2007-2019 (Only workers who took a wage cut when moving JTJ)



(a) Within a quarter



(b) Within a semester



(c) Within a year

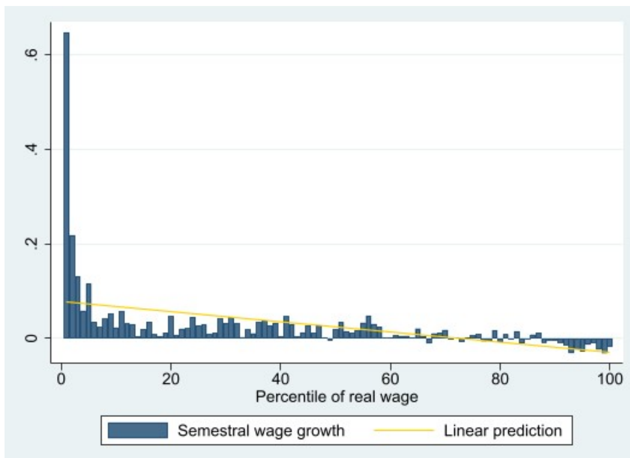
Source: Author' calculations using the UI registry database.

Despite this fact being interesting and robust, it cannot explain by itself why workers accept wage cuts when moving JTJ. This is, for example, because a *mover* can self-select into jobs that offer a combination of initial wage and wage growth that maximize her value of being employed, considering idiosyncratic preferences of workers. To avoid the latter, I control for observables that may mitigate the selection problem when workers move JTJ. In this regard, I propose a simple econometric specification that can help better understand the correlation between accepting wage cuts and future wage growth for job movers. For this purpose, I exploit the panel nature of the UI benefit database, which allows me to control for workers' heterogeneity using a fixed effects regression.

1.3.4 Accepted wage and growth rate facts

What is the relation between ex-post wage growth rates and the accepted wage that workers take when they do a JTJ transition? Figures 1.4 and 1.5 answer this question for two growth time spans, 6 and 12-month, respectively. Both figures plot the relationship between the accepted wage percentile and wage growth. The relation is clearly negative for both cases, where the correlation between these variables is -0.44 and -0.53 for Figures 1.4 and 1.5.

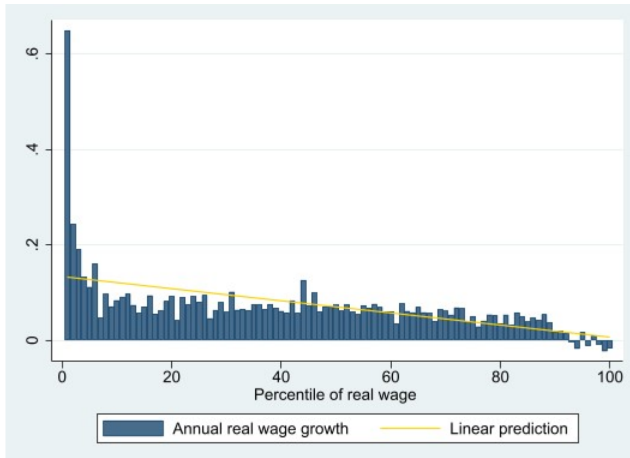
Figure 1.4: 6-month wage growth by accepted real wage percentile



Source: Author' calculations using the UI registry database.

It is worth noting that the percentile 1 shows an atypically high wage growth for both time spans, which is higher than 60%. I exclude this group of workers from the analysis and plotted the same relations in Figures 25 and 26 in the appendix.

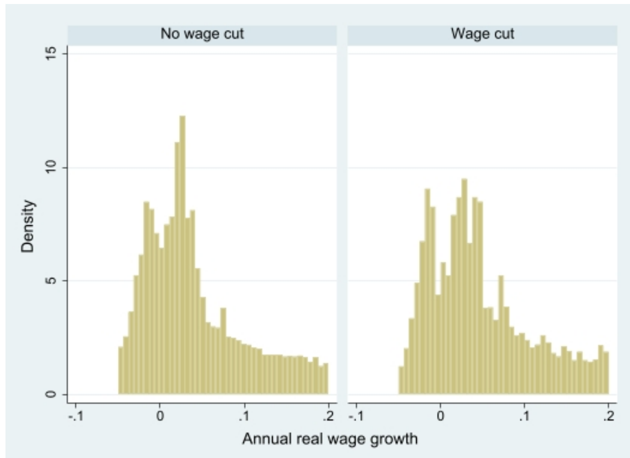
Figure 1.5: Annual wage growth by accepted real wage percentile



Source: Author' calculations using the UI registry database.

Another interesting fact is the difference in ex-post wage growth between wage cut takers and non-takers. For the whole sample, the average ex-post wage growth for the former is 9.5% and for the latter is 2.8%, with a difference of 6.7%, which is statistically significant. Although, the whole sample includes some outlier values and, therefore, high levels of dispersion. For this reason, Figure 1.6 plots the ex-post wage growth distribution for wage cut takers and non-takers, with both distributions truncated to leave out the extreme values. This modification yields an average ex-post wage growth for wage cut takers of 4.7% and for non-takers of 4%, a statistically significant difference.

Figure 1.6: Annual wage growth distribution

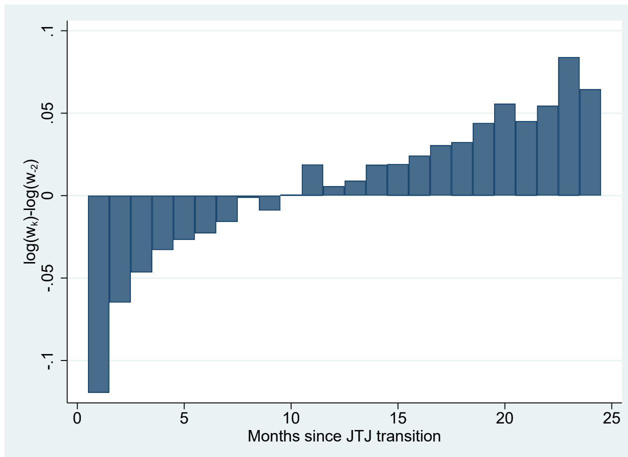


Source: Author' calculations using the UI registry database.

The latter analysis sheds light on the trade-off between current wage level and future wage growth that workers face when a job offer arrives. It seems that (i) workers enjoy higher wage growth in their destination firms when they accept a smaller wage offer, and (ii) wage cut takers enjoy higher wage growth rates than non-takers. As this evidence is only descriptive, in the following section I formalize the analysis by doing various econometric exercises.

Finally, in Figure 1.7 is displayed the comparison between the wage earned in the new firm with the last wage payment in their origin firms for wage cut takers. This relation is stated on the Y-axis of the figure and is given by the expression $log(w_k) - log(w_{-2})$, where k is the number of periods after a JTJ transition. From the figure, it can be observed that, on average, wage cut takers accept a payment that is 18% lower than the last wage they received at the origin firm. This gap declines systematically and it results in a positive gap starting in the 10th month after the job transition. In other words, workers take about 10 months on average to recover the wage level they experienced in their last job.
Afterwards, the gap starts to increase, meaning that workers experience real wage gains regarding their situation prior to the transition. By the second year (24th month) of working in a new firm, wage cut takers earn average real wages more than 5% higher than the last wage received in their prior job.

Figure 1.7: Difference between the k-th month wage earned after a JTJ transition and the last payment in the origin firm for wage cut takers.



1.3.5 Econometric Evidence

The first exercise I perform is defined by the following specification

$$\Delta log(w_{i,t+k}) = \alpha_i + \beta JTJ_{i,t} + \gamma \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \text{ for } k \in \{3, 6, 12\}, \tag{1.4}$$

where α_i is an individual fixed effect, $JTJ_{i,t}$ is a dummy that takes value 1 if worker i makes a JTJ transition in period t, and $\boldsymbol{X}_{i,t}$ is a vector that contains year, month and number of workers employed in the firm in which worker i is working in period t.

Table 1.2: JTJ transitions and ex-post real wage growth

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$JTJ_{i,t}$	0.005***	0.0053***	0.015***
Num. Obs	12,396,636	10,274,504	7,383,845
Num. Workers	274,369	247,253	200,982
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

The results of the estimation in (1.4) are displayed in Table 2. This evidence shows that, when accounting for workers' unobserved heterogeneity, JTJ transitions are positively associated with ex-post wage growth, that is, the growth experienced by workers' salaries in their destination firms after a JTJ transition. This result holds for my three measures of real wage growth, that is, JTJ transitions positively impact the wage growth rates for workers who make job transitions. This is true for the growth rate within 3, 6, or 12 months after the move.

The evidence in Table 2 sheds more light on the issue of the relation between job transitions and wage growth, and adds to what was analyzed in Figures 3-5. With this result in hand, one can be more convinced regarding the stylized fact in the exercise of *movers* versus *stayers* wage growth rates. Specifically, that *movers* exhibit higher wage growth rates than *stayers*. Nevertheless, we still have not explored if there is indeed a relationship between workers acceptance of wage cuts and their ex-post wage growth rates. For this purpose, I estimate the following econometric specification

$$\Delta log(w_{i,t+k}) = \alpha_i + \beta_1 wc_{i,t} + \beta_2 \boldsymbol{F}_{i,t-1} + \beta_3 \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t-1}, \text{ for } k \in \{3, 6, 12\}, \tag{1.5}$$

where $wc_{i,t}$ is defined as in equation (1.2), $\boldsymbol{F}_{i,t-1}$ is a vector that includes origin firm variables as controls, such as the log average wage that her origin firm pays to its workers, the log standard deviation of wages of her firm of origin, and the age of her firm of origin[6]. Vector $\boldsymbol{X}_{i,t-1}$ contains the same set of controls as in (1.4) but this time they are defined at period $t-1$, in order to control for the variables observed in the last period prior to making a JTJ transition. The results of specification (1.5) are displayed in Table 3.

The results in Table 3 show that there is a clear positive correlation between accepting a wage cut and the average real wage growth that JTJ movers experience ex-post. Workers who accept a wage cut when moving from one job to another experience three-month growth rates that are, on average, about 6.7% higher than that of those movers who see their real wage increase after the move. In the same fashion, workers who take wage cuts experience 6 and 12 month growth rates that are, on average, about 6.2% and 8.6% higher than that of those movers who do not take wage cuts. Besides, for variables of the origin firm, we have that the average wage paid in the origin firm is negatively correlated with wage growth in the destination firm, and the standard deviation of wages in the origin firm and its age have a negligent effect on the ex-post wage growth for the average job mover.

[6] Measured as the number of months that the firm is observed in the UI database in period t, that is, at the time of the job switch.

Table 1.3: Wage cuts and ex-post wage growth rate

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$wc_{i,t}$	0.067***	0.062***	0.086***
$log(w_{i,t-1})$	-0.034***	-0.043***	-0.12***
$log(\overline{w}_{j,t-1})$	0.013	0.004	0.004
$log(\sigma(w_{j,t-1}))$	-0.001	-0.002	-0.005
$Age_{j,t-1}$	0.0001*	0	0.0003**
Num. Obs	51,416	41,421	28,233
Num. Workers	41,953	34,852	24,789
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Besides, in order to have a better characterization of JTJ transitions that involve wage cuts, I propose the following specification

$$wc_{i,t} = \alpha_i + \beta_1 log(w_{i,t-k}) + \beta_2 \boldsymbol{F}_{i,t-1} + \beta_3 \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t-1}, \text{ for } k \in \{3,4,5\}, \quad (1.6)$$

where $log(w_{i,t-k})$ is the wage earned by worker i in her origin firm k periods prior to a JTJ move, and vectors $\boldsymbol{F}_{i,t-1}$ and $\boldsymbol{X}_{i,t-1}$ are defined the same as in (1.5). With this specification, the goal is to analyze which kind of worker is most likely to take a wage cut according to her earnings at her origin firm. Table 4 shows the results for equation (1.6). We have that the wage earned in the origin firm is positively correlated with taking a wage cut when moving JTJ. This result is robust to specifications that include controls for the origin firm and time dummies.

The idea behind using 3, 4, and 5 month lagged wages as an explanatory variable for accepting wage cuts follows from the fact that the UI registry database does not provide information about hourly wages. In that regard, it is feasible that in month $t-1$ (one month prior to a JTJ transition) the worker did not work the full month, and she perceived a monthly wage proportional to the days she went to work that month. Month $t-2$ is used directly to build the wage cut variable described in equation (1.2), thus it will be mechanically highly correlated with the dependent variable in (1.6). Therefore, using the wage lagged 3 months prior to a JTJ move avoids the latter two issues for the estimation described by (1.6). I also use the wages lagged 4 and 5 months as a robustness check of the result using the wage lagged 3 months.

The result in Table 4 provides intuition regarding the likelihood of a worker taking a wage cut according to the wage she earned in her origin firm. Specifically, it seems that workers who earn higher wages are more likely to take a wage cut when doing a JTJ transition. In this regard, this result seems reasonable since the higher a worker is in the job ladder, the less are the probabilities that an arriving job offer implies a higher starting wage than the current one. On the other hand, in order to interpret these results as evidence that workers accept wage cuts as a mechanism to enjoy other non-monetary benefits in a new job, I should -at least- have evidence that higher wages are associated with lower layoff probabilities.

Table 1.4: Taking wage cuts as a function of original wage. $log(w_{i,t-3})$ as variable of interest

	$wc_{i,t}$		
	(i)	(ii)	(iii)
$log(w_{i,t-3})$	0.12***	0.136***	0.173***
$log(\overline{w}_{j,t-1})$	-	-0.005	0.023
$log(\sigma(w_{j,t-1}))$	-	-0.002	-0.003
$Age_{j,t-1}$	-	-0.0002**	0
Num. Obs	67,398	61,259	61,259
Num. Workers	51,324	47,117	47,117
Year dummies	No	No	Yes
Month dummies	No	No	Yes
Workers dummies	No	No	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Table 1.5: Taking wage cuts as a function of original wage. $log(w_{i,t-4})$ as variable of interest.

	$wc_{i,t}$		
	(i)	(ii)	(iii)
$log(w_{i,t-4})$	0.128***	0.151***	0.186***
$log(\overline{w}_{j,t-1})$	-	-0.017	0.009
$log(\sigma(w_{j,t-1}))$	-	0.008	0.015
$Age_{j,t-1}$	-	-0.0001*	0.0001
Num. Obs	65,587	58,652	58,652
Num. Workers	50,168	45,327	45,327
Year dummies	No	No	Yes
Month dummies	No	No	Yes
Workers dummies	No	No	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Table 1.6: Taking wage cuts as a function of original wage. $log(w_{i,t-5})$ as variable of interest.

	$wc_{i,t}$		
	(i)	(ii)	(iii)
$log(w_{i,t-5})$	0.114***	0.135***	0.176***
$log(\overline{w}_{j,t-1})$	-	-0.007	0.026
$log(\sigma(w_{j,t-1}))$	-	0.013	0.016*
$Age_{j,t-1}$	-	-0.0002**	0
Num. Obs	63,867	56,355	56,355
Num. Workers	48,950	43,626	43,626
Year dummies	No	No	Yes
Month dummies	No	No	Yes
Workers dummies	No	No	Yes

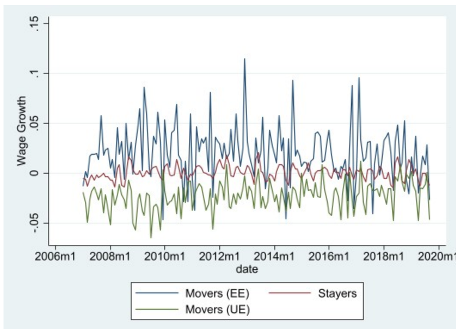
Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

1.3.6 Workers with Unemployment-Employment transitions

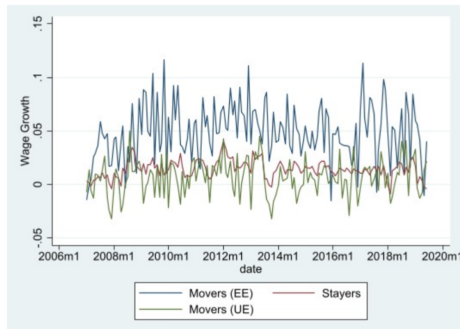
In order to have a better understanding of the trade-off between wage cuts and higher wage growth rates when moving JTJ, in this section I study the wage growth rates experienced by workers who make Unemployment-Employment (UE) transitions. Unemployed workers, generally, have lower reservation wage than employed workers, which consists principally in their unemployment insurance benefits. Thus, unemployed workers accept worse offers than employed workers. These offers may imply lower entry wages, lower wage growth rates or less atractive non-wage amenities, for example.

Regarding the latter, using the UI registry database I define a UE transition as a worker who has an employment gap greater than a month between two different employers. This definition of a UE transition is ad-hoc in the sense that the UI registry does not allow to observe workers who are unemployed because they go out from the database until they find another job in the formal sector. Because of this, I think that the assumptions behind the definition of a UE transition are rather weak.

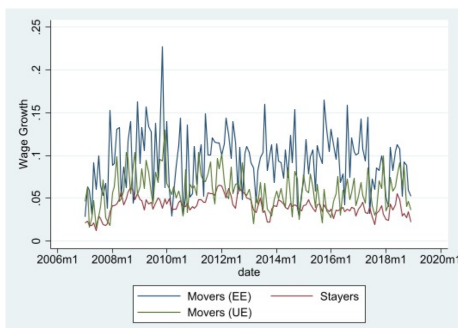
Figure 1.8: EE Movers vs stayers vs UE movers quarterly average wage growth (Only workers who took a wage cut when moving JTJ)



(a) Within a quarter



(b) Within a semester



(c) Within a year

Source: Author' calculations using the UI registry database.

Next, I perform the movers versus stayers exercise from Section 3.3, but adding the wage growth experienced by workers who make UE transitions. Figure 1.8 shows this analysis for the same three different cases of Section 3.3: within a quarter, within a semester, and within a year. Wage growth for JTJ movers is conditional on accepting a wage cut. The graphs that consider every JTJ mover are displayed in the appendix. From Figure 1.8, it seems that for every horizon, the JTJ movers experience higher ex-post wage growth rates than their UE transitioners counterpart. In fact, quarterly wage growth rates are 2.2% for JTJ movers and -2% for UE movers; wage growth rates within a semester are 4.9% for JTJ movers and 0.8% for UE movers; and wage growth rates within a year are 9.5% for JTJ movers and 5.9% for UE movers. Table 7 shows the results of mean differences tests between the latter worker flow categories. Column 1 displays the average ex-post wage growth for every JTJ mover; column 2 displays the average ex-post wage growth for JTJ movers that take a wage cut; column 3 displays the ex-post wage growth for UE movers;

column 4 displays the difference between column 1 and column 3; and column 5 displays the difference between column 2 and column 3.

Table 1.7: Mean differences for ex-post real wage growth: EE-UE

	$\Delta log(w_{i,t+3})$ (1)	$\Delta log(w_{i,t+3})$ ($wc_{i,t} = 1$) (2)	$\Delta log(w_{i,t+3})$ (workers UE) (3)	$[(1) - (3)]$	$[(2) - (3)]$
Mean	-0.0099	0.022	-0.022	0.012***	0.044***
	$\Delta log(w_{i,t+6})$ (1)	$\Delta log(w_{i,t+6})$ ($wc_{i,t} = 1$) (2)	$\Delta log(w_{i,t+6})$ (workers UE) (3)	(1) - (3)	(2) - (3)
Mean	0.014	0.049	0.008	0.006***	0.04***
	$\Delta log(w_{i,t+12})$ (1)	$\Delta log(w_{i,t+12})$ ($wc_{i,t} = 1$) (2)	$\Delta log(w_{i,t+12})$ (workers UE) (3)	(1) - (3)	(2) - (3)
Mean	0.058	0.095	0.059	-0.0011	0.036***

Notes: *** means that the t-statistic is > 2.96

Table 7 shows that for every specification JTJ movers experience higher wage growth rates than UE movers, and the differences are statistically significant. These differences range from 0.6% to 4.4%. The only case in which the difference is negative is for the annual ex-post wage growth difference between JTJ movers not conditioning in accepting a wage cut and UE movers, but this difference is not statistically significant.

This exercise shows that JTJ movers accept, on average, better offers than unemployed workers, possibly related to their reservation wage. These better offers allow JTJ movers to tradeoff lower entry wages for better job conditions that lead to higher wage growth rates. This is not possible for unemployed workers; since their outside option is being unemployed their job offer acceptance threshold is lower, therefore they will be willing to accept more and, generally, worse offers than employed job searchers.

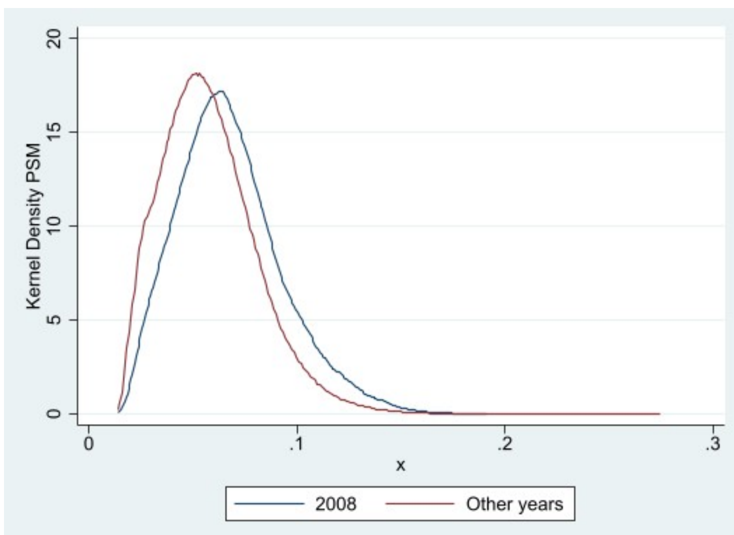
1.3.7 Robustness Checks

In order to properly interpret these results as evidence of taking wage cuts for an ex-post wage growth motive, the composition of jobs and workers should be unchanged over the business cycle. Otherwise, estimated changes in correlations between a JTJ transition and ex-post wage growth, and taking wage cuts and ex-post wage growth during the cycle may be generated by cyclical composition changes of job movers and/or firms. I address this possibility by controlling for compositional changes in the sample using the re-weighting technique of DiNardo, Fortin and Lemieux (1995) [17]. I implement the method by first choosing the composition of firms and workers in 2008, the year with a GDP growth (3.53%) closest to the sample average (3.06%), which spans from 2007 to 2019. After that, I run a probit model estimating the probability of being part of the 2008 sample as a function of observables on the workers' side X_i and on the firms' side, X_j. Variables included in vector X_i are: gender, age, age squared, married and educational level categories. Variables included in vector X_j are: economic sector and number of hired workers categories. Having defined the latter, I compute a predicted probability and define a weight for a worker i and a firm j pair in period t as

$$\varphi_{i,j,t} = \frac{\Phi(\gamma X_i + \delta X_j)}{1 - \Phi(\gamma X_i + \delta X_j)},$$

where $\Phi(\cdot)$ stands for the cumulative density of a standard normal distribution and γ and δ are estimates. The way to correctly implement this method is as follows: I consider that being in 2008 to be a treatment, and its probability to be a propensity score for treated (2008) and non-treated (not 2008) groups. Figure 1.9 depicts kernel estimates of these propensity scores densities. Due to the common support assumption (i.e, each observation must have a non-zero probability of being in both groups), I trim a very few number of observations that have extreme probabilities of being observed in 2008.

Figure 1.9: Estimated PSM for the DFL (1995) re-weighting compositional adjustment.



Source: Author' calculations using the UI registry database.

The results for this exercise are displayed in Tables 4, 5 and 6 in the Appendix. Overall, the results show that changing composition of the sample (pointing to aggregate conditions in labor markets which cannot be addressed by the data) by itself is not driving the results. Specifically, Table 4 shows that the facts of (i) JTJ transitions are associated with higher ex-post wage growth rates, (ii) wage-cut takers experience higher wage growth rates than non-takers and, (iii) workers with higher wages in their origin firms' are most likely to take wage cuts. This can be attributed to behavioral changes in workers, and not to compositional changes of firms or workers.

1.4 Conclusion

In this paper, I reassess the question regarding why workers accept wage cuts when a job offer arrives. So far, and to the best of my knowledge, the literature has studied three different reasons for this: (i) avoiding layoffs; (ii) match quality improvements; and (iii) investment in future wage growth. Using a large administrative database for Chile, which comes from the unemployment insurance registry, I build a monthly panel that spans from 2007 to 2019, and it allows me to follow the employment flows for more than 300,000 workers and analyze it to bring evidence on reason (iii).

I document several findings in JTJ transitions that are consistent with previous studies for Chile. First, I show that transition probability decreases as workers climb the wage ladder and that wage cuts when transitioning JTJ are rather pervasive, with more than 44% of JTJ transitions involving a wage cut. Then, I perform several descriptive exercises in order to understand the relationship between current wages and ex-post wage growth rates when workers face a job offer. The analysis of movers vs stayers shows that movers experience higher wage growth rates than stayers, which is interpreted as workers looking for better wage prospects when performing JTJ transitions. Furthermore, the difference between movers and stayers wage growth is even higher when I condition on workers accepting a wage cut when they perform a job transition. The latter evidence motivates a fixed-effects regression analysis, which confirms the stylized facts that were just mentioned. Specifically, job movers experience between 0.5% and 1.4% higher wage growth rates, depending on their growth horizon. Also, wage cut takers enjoy between 6.2% and 8.7% higher wage growth rates than those workers who increase their salary when moving JTJ. Finally, I explore the relationship between current wages (wages in the origin firm) and accepting wage cuts. This exercise shows that a 1% increase in current wages yields an increase in wage cut probability between 12 and 17%. Using the methodology of Dinardo, Fortin, and Lemieux (1995) [17], the results of the regression analysis are robust to changes in the composition of jobs and workers over time.

The empirical facts documented in this paper add to the literature on job transitions from two perspectives. First, I document that workers can make JTJ transitions as an instrument for climbing the wage ladder, not necessarily by accepting a higher initial wage, but by experiencing higher wage growth rates. Also, conditional to the latter, I assess the pervasiveness of wage cuts, explaining this phenomenon with the wage growth motive, which, at the same time, is able to complement the hypothesis of wage cuts as a function of *godfather shocks*. In this regard, my explanation suggests that wage cuts do not necessarily imply worsening a worker's value function when he makes a JTJ transition. Despite the latter, one can argue that wage growth is endogenous, and that it responds to, e.g., the match quality that a worker experiences in his destination firm, which is not observable and, thus, I could not assess with the data used in this article. Considering this, an interesting avenue for further research is the study of the relationship between match quality improvements and wage growth associated with JTJ transitions.

Chapter 2

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

2.1 Introduction

The ups and downs of commodity prices have caught wide attention on macroeconomists in the last two decades. Fernández, González and Rodríguez (2015)[23] 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, Kirchner and Yani (2015)[24] , Medina and Soto (2016)[36], Bodenstein et.al (2017)[7]). While this view of the effects of commodity price shocks seem, somehow, uncontested, there is still no a 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, we have 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)[7], 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.

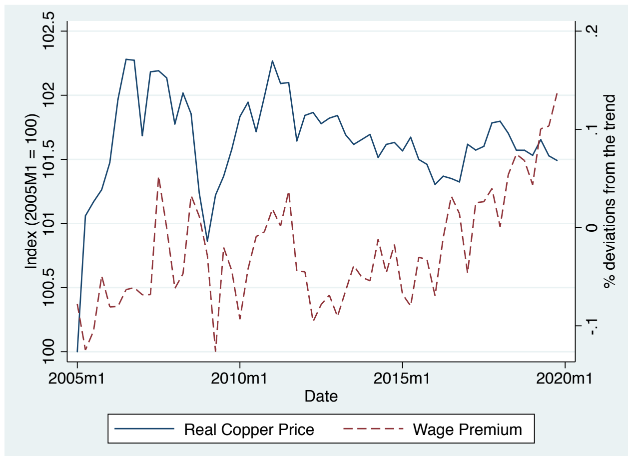
In this paper we address the question of which are the distributional consequences on labor market outcomes for heterogeneous workers (differing in their skill level) that arise from commodity price shocks, focusing in the institutional and demand channels of the shock propagation within the Chilean mining sector. We propose a structural model with heterogeneous workers and labor market frictions which allows us 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.

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[1]. 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 price boom period, which

[1]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.

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[2].

Figure 2.1: Copper price index (left) and detrended wage premium (right) .



Source: Chilean Unemployment Benefit database and Central Bank of Chile

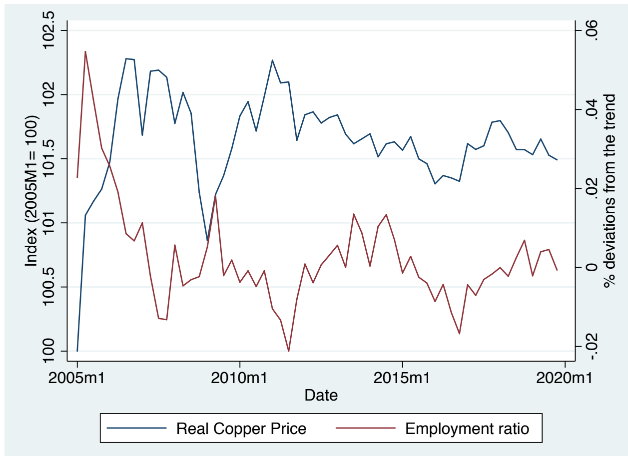
Regarding the relation between the employment ratio and the copper price over the business cycle for Chile, Figure 2 shows the detrended mining sector workers' H-to-L employment ratio and the copper price for the 2005-2019 time span[3]. In contrast with Figure 1, it seems that the relation between the 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[4].

[2]We 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.

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

[4]We also 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 2.2: 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)[27], Pellandra, (2015)[39] and Benguria, Saffie and Urzua, (2018)[6], in which commodity price shocks affect the wage premium and the employment ratio in the same way through a demand channel.

Our methodology to give an answer on the issue is, first, by using Chilean time series on the mining sector we 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, we 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, we propose a DSGE-SOE (Dynamic Stochastic General Equilibrium for a Small Open Economy) model in order to rationalize the findings of our SVAR exercise. Our 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 us 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)[18]). Skill intensity in commodity production allows us to account for the fact that commodity production is more intensive in low-skilled workers. We show that our simple model is capable to rationalize quite well the dynamics presented by the SVAR exercise. Finally, we explore how do SAM frictions and skill intensity in commodity production interact in our model, in order to provide a complete answer on how the commodity price shock is transmitted in our framework.

We 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 us 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 provides with an empirical motivation of our question of interest for the Chilean case with an SVAR exercise. Section 4 presents the DSGE-SOE model with heterogeneous SAM frictions which has the goal of rationalize the evidence provided in Section 3. Section 5 and 6 do the calibration strategy and the parameter estimation of the model, respectively. Section 7 does the analysis of the model economy, going deeper in the main transmission mechanisms that drive the results of our model. Section 8 concludes the results of this study and derives policy implications and avenues for further research.

2.2 Literature Review

Our study is related to two strands of the literature. The first one is that which studies the relation between commodity price shocks and labor market inequality focusing in Latin American countries. Benguria, Saffie and Urzua (2018)[6] use administrative data for Brazil from 1999 to 2013 and show that increases in regional commodity prices reduce the skill premium in that particular location. A paper that proposes a theoretical approach to give an answer on which is the mechanism that drives the declining skill premium in Latin America is Guerra-Salas (2018)[27]. He proposes a DSGE-SOE model with two productive sectors: tradables and non-tradables. Under the calibrated parameters, the model shows that a commodity price shock reallocates labor from the tradable to the non-tradable sector and, with the assumption that the non-tradable sector is more intensive in low-skilled labor, this reallocation of labor input yields a decline in the skill premium. Also, there are two papers that use data from Chile to explain how is labor market inequality affected by commodity price shocks, specifically, copper price shocks. The first one is Pellandra (2015)[39] which studies the effect of commodity boom on the wages and employment of skilled and unskilled workers in Chile between 2003 and 2011. He finds that a copper price shock in an industry that employs intensively employs unskilled labor (as the commodity sector does) reduces local wage premia proportionally more in regions where that industry represents a higher share of total employment compared to other regions. Specifically, empirical results show that a region exposed to a 10% increase in average commodity prices experienced a 2.4% increase in average unskilled workers' wages relatively to other regions, and that such gains contributed to a reduction in regional wage premia. Finally, Álvarez, García and Ilabaca (2017)[3] perform a natural experiment with Chilean microdata and show that copper price shocks contributed to decrease the poverty rate for the period 2003-2013, which represented the great commodity boom period. Besides, they explain that a channel for poverty reduction was that of improving unskilled workers labor market outcomes, where they show that commodity price shocks had a positive impact on employment and wages, but particularly for unskilled workers in mining industries. Our study adds to this literature using data from an administrative record for a time span that goes beyond the commodity price boom (which ended in 2011-2012) and focusing on the Chilean copper sector. Narrowing the analysis to only the commodity sector allows us to disentangle the effect of multiple channels that act at the same time when there is an unexpected commodity price shock. In particular, we can assess the dynamics of such a shock that are particular to the Chilean mining sector in order to compare the role of the demand and labor market institutional channel in the determination of employment and wage outcomes within the sector.

The second strand of the literature with which this paper relates is the one that embeds the standard Diamond, Mortensen, Pissarides (DMP) framework into a model of the business cycle. Early contributions of this are Andolfatto (1996)[4] and Merz (1995)[37]. However, open economy models rarely feature search and matching frictions in the labour market. Hairault (2002)[28] and Campolmi and Faia (2011)[11] show how augmenting a standard open economy model by the DMP framework impacts the transmission of shocks across countries. Christiano et al. (2011)[14] develop a detailed small open economy DSGE model with search and matching frictions that can be employed for policy analysis. Boz et al. (2009)[9] study search and matching frictions in a small open economy model calibrated to Mexican data. Bodenstein et.al., (2017)[7] investigate empirically and theoretically the connection between commodity price shocks and unemployment in advanced resource-rich small open economies within a DMP framework. They find that shocks to commodity prices are shown to influence labour market conditions primarily through the real exchange rate, whereas a positive price shock is found to expand the components of GDP, to cause the real exchange rate to appreciate, and to improve labour market conditions. We contribute to this strand by adding heterogeneity in workers' skills in the spirit of e.g., Dolado et al. (2021)[18]; Wolcott (2021)[47]; Abbritti and Consolo (2022)[1]. Workers with different skills face different labor market frictions and, also, they are employed with different intensity in the commodity production[5]. This framework allows us to rationalize the empirical fact documented here which states that, for the Chilean mining sector, the employment ratio and the wage premium exhibit a negative correlation in response to a copper price shock.

2.3 Commodity Price Shocks and Labour Market Outcomes Gap: SVAR Evidence

In order to motivate out research question, we 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. We construct 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, we 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: we calculate wages and employment levels by skill level by obtaining quarterly averages for these variables from 2005:M1-2019M10. We classify workers 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[6].

We examine quarterly data covering the sample period between January 2005

[5]To illustrate, low-skilled workers represent more than 60% of the total mining sector workforce in Chile but, on the other hand, the mining sector is highly intensive in capital, which shows higher degrees of complementarity with high-skilled workers rather than with low-skilled workers.

[6]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. We could not use use information for hours worked because the UI database does not contain that variable.

to October 2019. We 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, we exclude years 2002, 2003 and 2004 from the sample because, as Cruz and Rau (2021)[16] 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 and Carranza (2015)[41] 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 we 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 us with less observations to perform the analysis, is that we decided to follow Cruz and Rau (2021)[16] 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[7]. This implies that for 80% of mining workers we observe their complete wages, while for the rest we only observe that they earn a wage that is above the cap, but not the received monthly wage itself. Disaggregating by skill level, we have that 41% and 15% of high and low-skilled workers, respectively, have their wages capped.

Our SVAR consists of seven variables: real GDP, the vacancy creation index, 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 (2015)[24], we 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, we 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

[7]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.

$\boldsymbol{D}$. 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, we impose that $\boldsymbol{A}_2 = 0$ such that y_1 forms an exogenous block of variables (which will be subject to the identification scheme that we describe below).
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) we include one lag of each variable in the VAR.

The strategy that we 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 high-skilled employment rate whereas this variable affects the high-skilled real wage rate, and finally this las variable affects the wage premium. In more detail, the vector of orthogonalized shocks, $\boldsymbol{\nu}_t$, is defined by

$$\boldsymbol{\nu}_t = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_{pCO} \\ \varepsilon_{GDP} \\ \varepsilon_{vac} \\ \varepsilon_{emp} \\ \varepsilon_{wage}. \end{pmatrix}$$

In what follows, we present two different SVAR exercises. First, we 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. This will give us 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 will provide us with the different impacts that the commodity and non-commodity sectors experience after a commodity (copper, specifically) price shock. That is, we will be able to explore if there is any difference in how the employment ratio and the wage premium react in both sectors.

2.3.1 SVAR for the mining sector

Figure 2.3: IRFs to an unexpected increase in the international copper price.

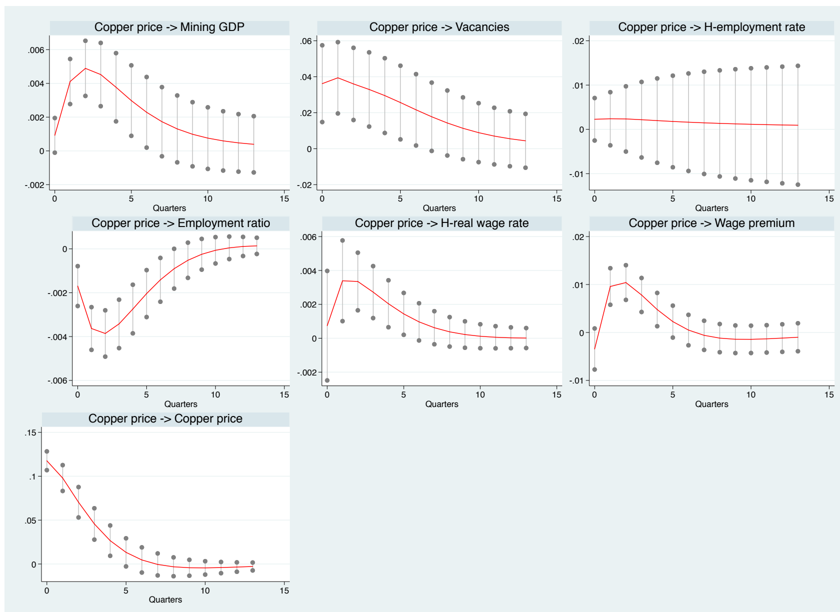


Figure 3 displays point estimates and 68 percent confidence intervals for the impulse response functions (IRFs) of the baseline SVAR model to the identified real copper price shock. The shock has expansionary effects. After the unexpected copper price increase, total GDP increases persistently. Regarding 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 24 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.

2.3.2 SVAR for the non-mining sector

Figure 2.4: IRFs to an unexpected increase in the international copper price.

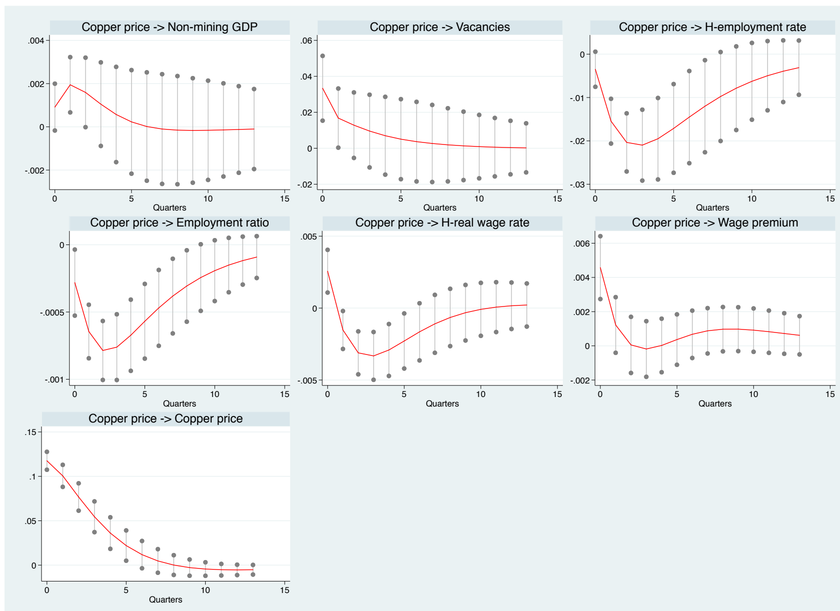


Figure 4 displays point estimates and 68 percent confidence intervals for the impulse response functions (IRFs) of the counterfactual SVAR model to the identified real copper price shock considering labor market variables for workers outside the mining sector. The results are similar with the ones presented 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 Alvarez et. al (2017)[3] and add that they do not make the difference we 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 Alvarez et.al (2017)[3], 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 we 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.

2.4 The Model

Our model belongs to the family of DSGE models with SAM frictions for an small open economy (SOE), which we will refer to as DSGE-SOE. We omitted the New Keynesian feature from the model because our 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 allow us 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 in workers that belong to the commodity sector. We model this heterogeneity as follows: each household has a fixed proportion of low skilled labor market participants, which may be employed or unemployed. This proportion is called π, therefore we will have that each household has a fixed proportion $(1 - \pi)$ of high-skilled labor market participants. The latter is depicted in Figure 25 in the appendix.

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, we 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.

2.4.1 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

$$u_t^\ell = \pi x - (1-\delta_t)N_{t-1}^\ell, \tag{2.1}$$

and

$$u_t^h = (1-\pi)x - (1-\delta_t)N_{t-1}^h \tag{2.2}$$

where we have assumed 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

$$\ln(\delta_t) = (1-\rho_\delta)\ln(\bar{\delta}) + \rho_\delta \ln(\delta_{t-1}) + \varepsilon_{\delta,t}, \tag{2.3}$$

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

$$m_t^h = \mu_h (u_t^h)^\alpha (v_t^h)^\alpha \tag{2.4}$$

and

$$m_t^\ell = \mu_\ell (u_t^\ell)^\alpha (v_t^\ell)^\alpha, \tag{2.5}$$

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 we 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

$$N_t^h = (1-\delta_t) N_{t-1}^h + m_t^h, \tag{2.6}$$

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

$$N_t^\ell = (1-\delta_t) N_{t-1}^\ell + m_t^\ell. \tag{2.7}$$

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

$$U_t^h = (1-\pi)x - N_t^h, \tag{2.8}$$

and low-skilled unemployment is given by

$$U_t^\ell = \pi x - N_t^\ell. \tag{2.9}$$

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

$$p_t^h = m_t^h / u_t^h, \tag{2.10}$$

and the job finding probability for low-skilled workers as

$$p_t^\ell = m_t^\ell / u_t^\ell. \tag{2.11}$$

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

$$q_t^h = m_t^h / v_t^h, \tag{2.12}$$

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

$$q_t^\ell = m_t^\ell / v_t^\ell, \tag{2.13}$$

2.4.2 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. We 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:

$$\begin{aligned}\mathcal{V}(N_t^h, N_t^\ell) = \max_{N_t^h, N_t^\ell, v_t^h, v_t^\ell} p_t^{co} F(N_t^h, N_t^\ell) - \\ \sum_{k\in\{h,\ell\}} (w_t^k N_t^k + \kappa^k v_t^k) + \mathbb{E}_t[\Lambda_{t+1}\mathcal{V}(N_{t+1}^h, N_{t+1}^\ell)]\end{aligned} \tag{2.14}$$

subject to

$$N_t^k = (1-\delta)N_{t-1}^k + m_{t-1}^k, \; k \in \{h, \ell\}, \tag{2.15}$$

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

$$F(N_t^h, N_t^\ell) = Y_t^{co} = Z_t(HN_t^h)^{\alpha_h}(N_t^\ell)^{1-\alpha_h}, \tag{2.16}$$

where Z_t denotes a technology shock, and H is an idiosyncratic productivity parameter for high-skilled workers such that $H > 1$, and $\alpha_h \in (0, 1)$ is a skill-intensity parameter. The technology shock Z_t follows the stochastic process

$$\ln Z_t = (1-\rho_z)\ln(\bar{Z}) + \rho_z \ln Z_{t-1} + \varepsilon_{z,t}. \tag{2.17}$$

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

$$V_t^\ell = -\kappa_\ell + q_t^\ell \mathbb{E}_t[\Lambda_{t+1}(1-\delta_{t+1})J_{t+1}^\ell + \delta_{t+1})V_{t+1}^\ell]. \tag{2.18}$$

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

$$V_t^h = -\kappa_h + q_t^h \mathbb{E}_t[\Lambda_{t+1}(1-\delta_{t+1})J_{t+1}^h + +\delta_{t+1})V_{t+1}^h]. \tag{2.19}$$

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

$$J_t^\ell = p_t^{co}\frac{(1-\alpha_h)Y_t^{co}}{N_t^\ell} - w_t^\ell + \mathbb{E}_t\Lambda_{t+1}[\delta_{t+1}V_{t+1}^\ell + (1-\delta_{t+1})J_{t+1}^\ell], \tag{2.20}$$

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

$$J_t^h = p_t^{co}\frac{\alpha_h Y_t^{co}}{N_t^h} - w_t^h + \mathbb{E}_t\Lambda_{t+1}[\delta_{t+1}V_{t+1}^h + (1-\delta_{t+1})J_{t+1}^h], \tag{2.21}$$

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

$$\frac{\kappa_h}{q_t^h} = \mathbb{E}_t\left[\Lambda_{t+1}(1-\delta_{t+1})\left(p_{t+1}^{co}\frac{\alpha_h Y_{t+1}^{co}}{N_{t+1}^h} - w_{t+1}^h + \frac{\kappa_h}{q_{t+1}^h}\right)\right], \tag{2.22}$$

and

$$\frac{\kappa_\ell}{q_t^\ell} = \mathbb{E}_t\left[\Lambda_{t+1}(1-\delta_{t+1})\left(p_{t+1}^{co}\frac{(1-\alpha_h)Y_{t+1}^{co}}{N_{t+1}^\ell} - w_{t+1}^\ell + \frac{\kappa_\ell}{q_{t+1}^\ell}\right)\right], \tag{2.23}$$

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.

2.4.3 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, we 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. 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

$$Y_t^c = Z_t(1-x) \tag{2.24}$$

2.4.4 The Representative Household

The representative household has the utility function

$$\mathbb{E}_t\Big[\sum_{t=0}^{\infty}\beta^t\Theta_t(ln(C_t)-\chi(N_t^h+N_t^\ell))\Big], \tag{2.25}$$

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 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

$$\ln\theta_t = \rho_\theta \ln\theta_{t-1} + \varepsilon_{\theta,t}, \tag{2.26}$$

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

$$C_t + D_t^* = r_t D_{t-1}^* + w_t^h N_t^h + w_t^\ell N_t^\ell + \phi(x - N_t^h - N_t^\ell), \forall t \geq 0, \tag{2.27}$$

where r_t denotes the interest rate that is carried by the foreign debt, and ϕ measures the unemployment benefits, which we 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

$$r_t = a + z_t^r + \psi(e^{\hat{D}_t^* - \bar{D}^*} - 1), \tag{2.28}$$

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

$$\ln(z_t^r) = (1 - \rho_{zr}) \ln(\bar{z}^r) + \rho_{zr} \ln(z_{t-1}^r) + \varepsilon_{t,zr}. \tag{2.29}$$

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

$$B_t(D_t^*, N_t^h, N_t^\ell) = \max_{C_t, N_t^h, N_t^\ell, D_t^*} lnC_t - \chi(N_t^h + N_t^\ell) + \beta \mathbb{E}_t \theta_{t+1} B_{t+1}(D_{t+1}^*, N_{t+1}^h, N_{t+1}^\ell), \tag{2.30}$$

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

$$S_t^k = w_t^k - \phi - \frac{\chi}{C_t} + \mathbb{E}_t \Lambda_{t+1}(1 - q_{t+1}^k)(1 - \delta_{t+1}). \tag{2.31}$$

2.4.5 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

$$\max_{w_t^k} (S_t^k)^b (J_t^k - V_t^k)^{1-b}, \tag{2.32}$$

where $b \in (0, 1)$ denotes the bargaining power for workers, which is the same within workers' types.

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

$$\frac{b}{1-b}(J_t^k - V_t^k) = w_t^k - \phi - \frac{\chi}{\Lambda_t} + \mathbb{E}_t \Lambda_{t+1}(1 - q_{t+1}^k)(1 - \delta_{t+1}) \frac{b}{1-b}(J_{t+1}^k - V_{t+1}^k) \tag{2.33}$$

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

$$w_t^h = b^h \underbrace{(p_t^{co}\frac{\alpha_h Y_t^{co}}{N_t^h} + \kappa_h\theta_h)}_{\text{PMg-h + hiring costs}} + (1-b^h)\underbrace{(\phi + \chi^h C_t)}_{\text{Outside option}} \tag{2.34}$$

and,

$$w_t^\ell = b^\ell \underbrace{(p_t^{co}\frac{(1-\alpha_h) Y_t^{co}}{N_t^\ell} + \kappa_\ell\theta_\ell)}_{\text{PMg-}\ell\text{ + hiring costs}} + (1-b^\ell)\underbrace{(\phi + \chi^\ell C_t)}_{\text{Outside option}} \tag{2.35}$$

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, $\chi^k C_t$.

2.4.6 Commodity price and production

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

$$Y_t^{co} = F(N_t^h, N_t^\ell), \tag{2.36}$$

which describes the commodity production in each period. We 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

$$\ln(p_t^{co}) = (1-\rho_{p^{co}})\ln(\bar{p}^{co}) + \rho_{p^{co}}\ln(p_{t-1}^{co}) + \varepsilon_{t,p^{co}}, \tag{2.37}$$

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 we leave that feature aside because we want 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.

2.4.7 Government policy

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

$$T_t = \phi(x - N_t^h - N_t^\ell). \tag{2.38}$$

2.4.8 Market clearing and search Equilibrium

We can define the trade balance as

$$TB_t = (1-\gamma)p_t^{co}Y_t^{co}. \tag{2.39}$$

Consumption spending has to be equal to consumption goods production plus the fraction of the commodity good that is consumed by the households. That is,

$$C_t = Y_t^c + \gamma Y_t^{co}. \tag{2.40}$$

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

$$Y_t = C_t + \sum_{k\in\{h,\ell\}} \kappa_k v_t^k + TB_t. \tag{2.41}$$

Finally, the net foreign asset position evolves according to

$$D_t^* = r_t D_{t-1}^* + TB_t. \tag{2.42}$$

2.5 Parametrization Strategy

Our 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, we estimate the remaining structural parameters and some shock processes in order to fit Chilean time-series data.

2.5.1 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 we 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 and Liu (2019)[34]. 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 we used to calibrate the value of π. The elasticity of the matching function, α, is assumed to be the same for high and low-skilled workers, and we took the value estimated for this parameter in Guerra-Salas et al. (2018)[27], 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)[5], Wolcott (2021)[47], Eeckhout and Kircher (2018)[21] and Dolado et al., (2021)[18], 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)[18] calibrates matching efficiencies in order to help the calibration of the remaining parameters; we follow this same approach for these parameters.

Table 2.1: 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 (2018)
α_h	Skill-intensity parameter for the commodity production	0.32	Dolado et.al., (2021)/ Benguria, Saffie and Urzua (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)
H	h-workers idiosyncratic productivity	1.7	Endogenous
π	ℓ-workers proportion within the household	0.676	CASEN survey
$U^\ell/\pi x$	ℓ-workers unemployment rate in SS (% of $\ell - workforce$)	0.08	-
$U^h/(1-\pi)x$	h-workers unemployment rate in SS (% of h-workforce)	0.08	-
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 (2017)
$\bar{z}^r$	Annual steady state EMBI spread 2005-2019	1.4%	BCCh
ψ	Risk premium parameter	0.0007	Guerra-Salas (2017)
$\bar{TB}/Y$	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 (2017)
σ_Z	std.dev of technology shock	0.035	-
σ_{zr}	std.dev of spread shock	0.17	Guerra-Salas (2017)

Vacancy posting costs are different between high and low-skilled workers. We did not use any calibration of these parameters in the literature because, to our knowledge, there is little evidence on this, and no direct evidence for Chile. Dolado et.al (2021)[18] 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 et al. (2010)[19] 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)[47] takes this evidence and estimates that $\kappa_h = 0.6$ and $\kappa_\ell = 0.2$. Besides, intuitively we may consider that, 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. We used the latter reasoning joint with the calibration of H, which is the parameter that measures h-workers idiosyncratic productivity, 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, $\bar{\delta}$, we follow Jones and Naudon (2009)[32], 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)[26]).

We target a steady state unemployment rate for both types of workers. We do this 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, we 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 we could not disentangle the unemployment rate for different worker types according to their skill (education) level, we 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)[18]).

For the Nash bargaining power parameters we used two different -but complementary- criteria in order to do the calibration. First, we look at the related literature (Cahuc et al., (2006)[10]; Dolado et al., (2021)[18]) 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. We 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, we 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[8] 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%[9]. Summarizing, we calibrate b^k for $k \in \{h, \ell\}$, such that $b^k > 0.5$, which is the

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

[9] 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.

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.

2.6 Estimation

The parameters that govern the exogenous processes that act as driving forces of fluctuations in the model economy are estimated using Bayesian techniques. For this purpose, we use HP filtered series of quarterly data and log demeaned for h and ℓ real wage rates for the mining sector, consumption and real GDP, which are used as observable variables. Wage series were extracted from the unemployment insurance database, whereas consumption and real GDP series were 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 0.7 and standard deviation 0.1 assumed 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 $\sigma_{_{co}}$, σ_θ 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 we decided not to estimate these parameters was because of identification issues for them conditional to the observed variables that we use for the estimation. Given the latter, these parameters were calibrated according to the information in Table 1.

Table 2.2: Estimated Parameters

		Priors		Posteriors	
	Parameter description	Type	[mean, std]	Mean	90% HPDI
$\rho_{p_{co}}$	Copper price shock persistence	Beta	[0.7, 0.1]	0.5861	[0.4529, 0.7263]
ρ_{θ}	Preference shock persistence	Beta	[0.7, 0.1]	0.8509	[0.7693, 0.9354]
ρ_{Z}	Tech.shock persistence	Beta	[0.7, 0.1]	0.7621	[0.6449, 0.8854]
ρ_{δ}	Job separation shock persistence	Beta	[0.7, 0.1]	0.5306	[0.4117, 0.6438]
σ_{co}	std of preference shock	Inv.Gamma	[0.01, Inf]	0.5789	[0.4894, 0.6644]
σ_{θ}	std of preference shock	Inv.Gamma	[0.01, Inf]	1.5683	[1.2002, 1.9153]
σ_{δ}	std of job separation shock	Inv.Gamma	[0.01, Inf]	16.983	[14.4133, 19.404]

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 25%. HPDI are the highest posterior density intervals. The computations were made using Dynare 4.6.4.

2.7 Analysis of the Model Economy

Based on the calibrated and estimated parameters, we 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 our main focus in order to understand how does this kind of impulse affect labor market gaps between high and low-skilled workers.

2.7.1 Non-Commodity price dynamics

Figure 3 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 our parameterization, high-skilled workers are more affected relatively, which yields a decrease in the wage premium as well. Besides, consistently with Shimer (2005)[42], the job separation shock raises both unemployment and vacancies for both types of worker, which mechanically boosts hiring through the matching function[10].

[10]Shimer (2005)[42] 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 2.5: IRFs to a shock in ε_δ

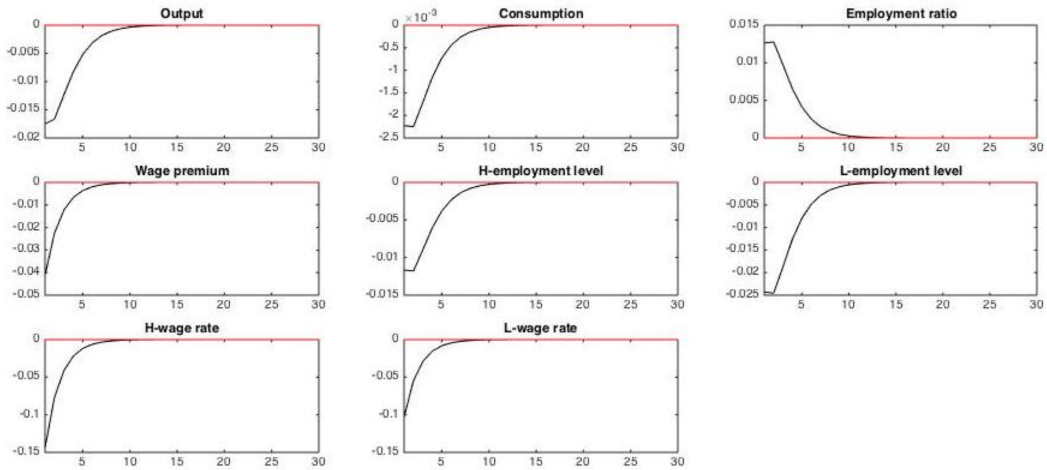


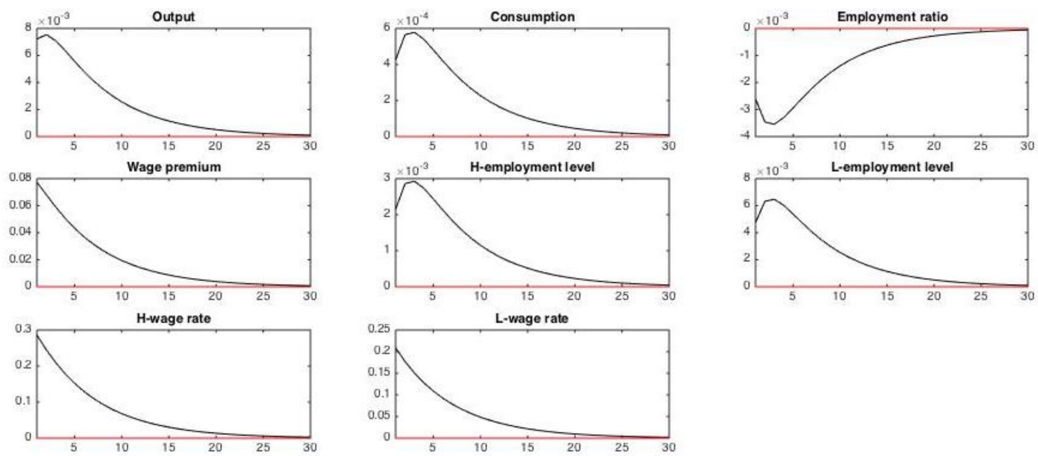
Figure 4 shows the impulse responses to a positive technology shock. The shock leads to an increase in both types of employment, but it is low-skilled labor which benefits the most, which results in a decrease in the employment ratio. As employment levels raise, both aggregate production and consumption 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 2.6: IRFs to a shock in ε_z

z_irf.jpg

Figure 5 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 our 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.

Figure 2.7: IRFs to a shock in ε_θ



2.7.2 Variance Decomposition

In this section we explore the relative role of the different shocks that we include in the model to explain movements in key variables. We do this by presenting the unconditional forecast error variance decomposition (FEVD) for a selected set of variables.

Table 3 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 job separation 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)[26]).

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 93% of the variation of employment for high and low-skilled workers. This contrasts with Shimer (2005)[42], who argues that, in the U.S, job creation is the main cyclical driver of (un)employment. Nevertheless, Elsby, Hobijin and Sahin (2013a)[22] 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 Konya (2016)[30] find that separation shocks account for two-thirds of the employment variation in their model. Our result is, therefore, closer to these evidence than to Shimer (2005)[42].

Table 2.3: Forecast Error Variance Decomposition

Variables	Job separation shock	Technology shock	Discount factor shock	Copper price shock	interest rate shock
Y	21.08	62.46	4.41	12.05	0
N^h/N^ℓ	92.37	0	7.42	0.21	0
w^h/w^ℓ	4.88	0.46	25.53	69.13	0
N_t^h	93.76	0	6.04	0.2	0
N_t^ℓ	93.05	0	6.74	0.2	0
w_t^h	7.24	0.34	41.06	51.35	0
w_t^ℓ	8.46	0.28	49.56	41.7	0

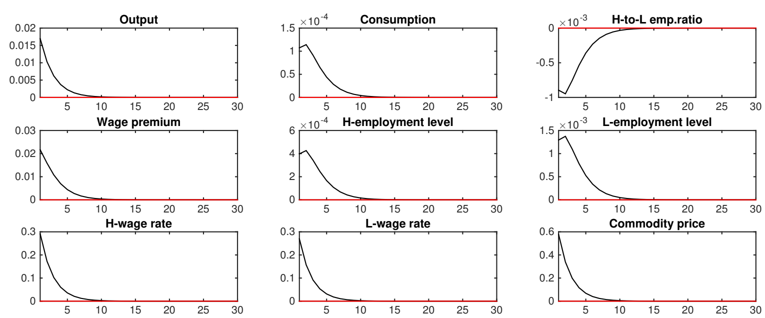
Note: The numbers reported are the posterior mean contributions (in percentage terms) of each of the four shocks in the estimation to the forecast error variances of the variables listed in each row.

Despite of the latter, the job separation shock explains a negligible part of the variation of wages, and that of the wage premium, which is consistent with the evidence in Jakab and Konya (2016)[30] and Guerra-Salas et al. (2021)[26]. 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 and Liu (2019)[34]). Thus, they are important for explaining the the observed labor market fluctuations (Hall (2017)[29]). Quantitatively, the variance decomposition shows that the discount factor shock contributes to about 45% of the variation of wages, on average, a 25% of the variation in the wage premium, and about a 6% 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 et al. (2018)[27] explains 6% of GDP variation, 12% of wage variation, and 6% of employment variation. As we endogenized the commodity production, it is natural that the commodity price shock explains a larger fraction of aggregate production and wages in our model, with about a 12% and 45% respectively. Besides, it explains almost a 70% of the wage premium variation in the commodity sector.
Finally, the foreign interest rate shock plays almost no role in explaining the variance of the endogenous variables of our model. This is consistent with the evidence of the role of interest rate spread shocks in Guerra-Salas (2018)[27] and Guerra-Salas et al. (2021)[26].

2.7.3 Positive shock in the commodity price

Figure 6 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. We can see 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 our 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 2.8: IRFs to a shock in $\varepsilon_{p^{co}}$.



Comparing the result in Figure 2 with the empirical one in Section 2 we have that our model, qualitatively, reproduces well the dynamics found by the SVAR exercise. Despite of this, we are not trying here to match exactly the dynamics showed by the SVAR. This is because we 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, we 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)[27] 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)[18] 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)[27], where the source of the shock is the same that we emphasize on here and the results, qualitatively speaking, are not the same.

In order to place our results in the literature we 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 we made above. That is, we are 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 we 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, we construct next four cases to compare with our 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.

Skill-intensity benchmark

Figure 9 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 9 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 $\partial WP_t/\partial p_t^{co} < 0$[11]. The wage premium decreases monotonically as b^h decreases.

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

Figure 2.9: Wage premium sensitivity for different b^h and the benchmark skill-intensity, α_h

wp_bh.jpg

The other search parameter that is directly related to wages is the vacancy creation cost, κ_k. In order to analyze the wage premium we will consider variations in κ_ℓ. The intuition is that as κ_ℓ increases, the wage premium is supposed to decrease. Figure 10 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 tells us that the wage premium is more sensitive to variations in b^h than in κ_ℓ.

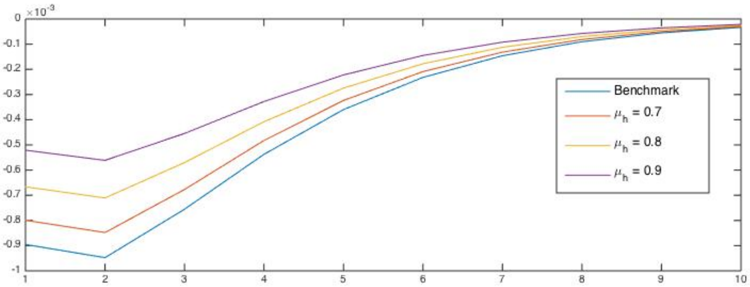
Even though, regarding the calibration section, we stated that the literature stands for $b^h > b^\ell$ and $\kappa_h > \kappa_\ell$, the latter exercise is useful to have some quantitative approach to understand how much must the search parameters increase (or decrease) in order to produce IRF increasing 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 we 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 we 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.

Figure 2.10: Wage premium sensitivity for different κ_ℓ and the benchmark skill-intensity, α_h

wp_kappal.jpg

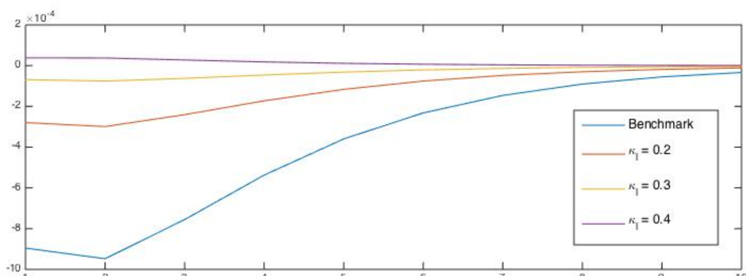
The employment ratio is principally affected by two sub-sets of search parameters: μ_k and κ_k, for $k \in \{h, \ell\}$. Figures 11 and 12 display the employment ratio comparative statics for μ_h and κ_ℓ, respectively. Figure 11 shows that the employment ratio increases monotonically when μ_h increases, 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 $\mu_h = 0.9$.

Figure 2.11: Employment ratio sensitivity for different μ_h and the benchmark skill-intensity, α_h



Finally, Figure 12 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 we 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.

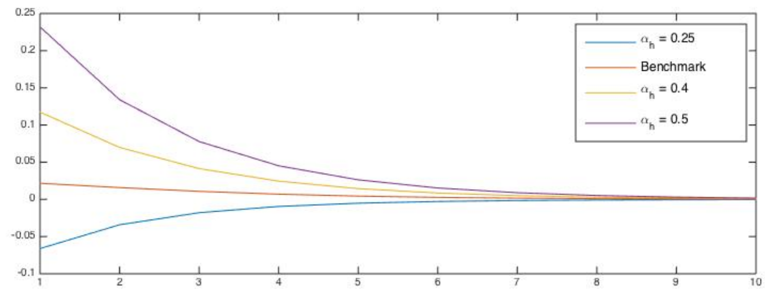
Figure 2.12: Employment ratio sensitivity for different κ_ℓ and the benchmark skill-intensity, α_h



SAM frictions benchmark

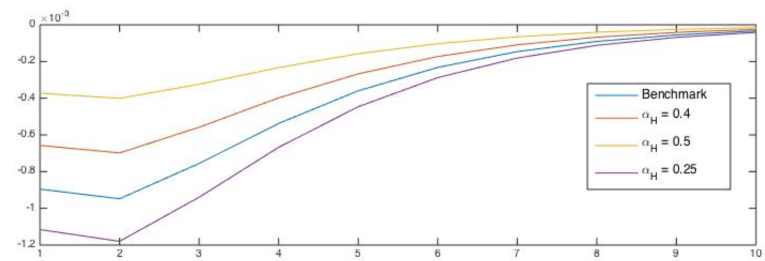
Figures 13 and 14 display the sensitivity of the wage premium and the employment ratio, respectively, with respect to the skill-intensity parameter, α_h. A 22% decrease in α_h (w/r to the benchmark) implies that the wage premium IRF decreases about 8 p.p on impact, and it yields that $\partial WP_t/\partial p_t^{co} < 0$. The latter implies that the benchmark value of $\alpha_h = 0.32$ might be a lower bound for the skill-intensity parameter in our framework, in the sense that a slight decrease would yield a wage premium IRF in the opposite direction with respect to our SVAR analysis. Also, increases of α_h w/r the benchmark value monotonically increases the wage premium, as expected.

Figure 2.13: Wage premium sensitivity for different α_h and the benchmark SAM friction parameters



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.

Figure 2.14: Employment ratio sensitivity for different α_h and the benchmark SAM friction parameters



As our 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 our framework should be understood as taking account of the capital-skill complementarity that was not modeled here, therefore, it would be likely that $\alpha_h > 0.32$, which would imply a higher on-impact value for the wage premium and employment ratio IRFs as displayed in figures 13 and 14. Of course, the right way to assess this is to include capital-skill complementarity to our framework.

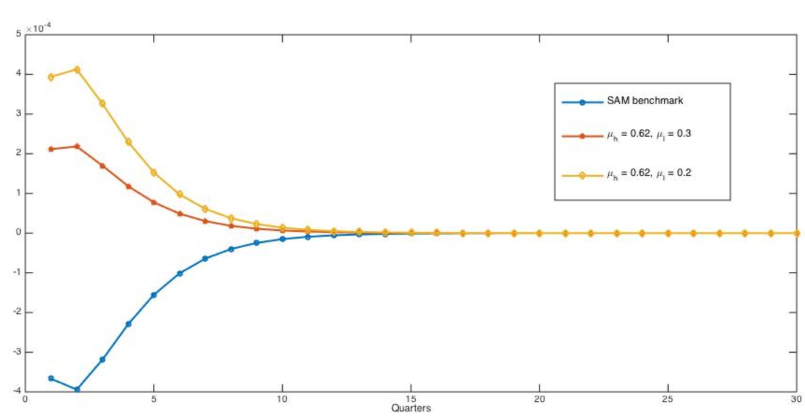
Only asymmetric SAM frictions

in this section, in order to understand in a better way the transmission mechanism of our model, we suppress the heterogeneity in skill intensity in the commodity production. Doing so allows us to study what is the effect of changing parameters associated with the SAM frictions in our model and analyze its effects in labor market gaps between high and low-skilled workers. That is, we 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 we will only change one labor market parameter corresponding to one skill type or the other. The reason on doing this exercise is that we want to explore how do labor market gaps change when the baseline conditions in the labor market change as well. That is, we focus on increasing the difference in matching efficiency, bargaining power, and vacancy posting costs, among the different workers' skill types.

Figure 15 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 we will analyze different IRFs for the employment ratio for the case where μ_ℓ decreases.

Figure 2.15: IRFs of the employment ratio for different matching efficiencies, μ_k



From Figure 15, we can observe, 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 we 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 happens in Figure 7 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 16 shows the IRFs for the wage premium when the labor market is described by different matching efficiencies, as we 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

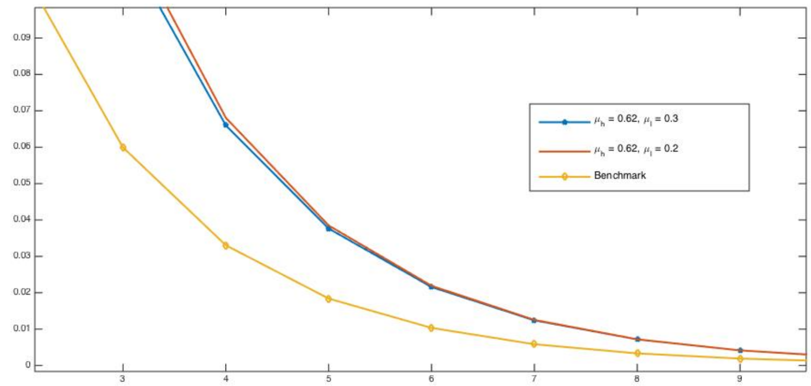
$$PMg_t^k = \begin{cases} \frac{\alpha_h Y_t^{co}}{N_t^h}, \text{ if } k = h, \\ \\ \frac{(1-\alpha_h) Y_t^{co}}{N_t^\ell}, \text{ if } k = \ell, \end{cases}$$

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

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

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 we 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 8 shows.

Figure 2.16: IRFs of the wage premium for different matching efficiencies, μ_k



Now turning to study labour market differences when changing the bargaining power differential between workers' types, Figure 17 shows how the wage premium is affected when we increase b^h 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 9 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 2.17: IRFs of the wage premium for different H-bargaining power, b^h

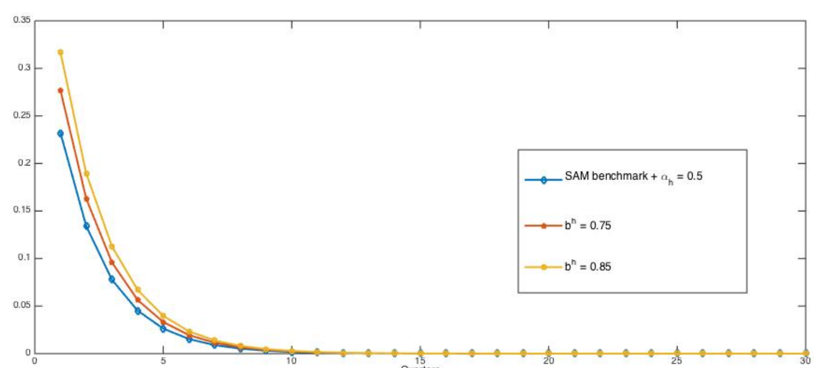
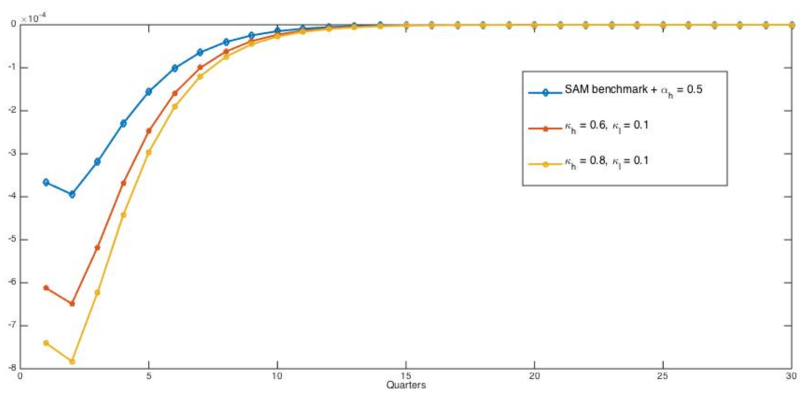


Figure 18 shows the employment ratio dynamics when having different high-skilled vacancy posting costs. In particular, in this exercise we increase κ_h in order to understand how is the employment ratio affected when high-skilled vacancies are more expensive than in the benchmark case. Again, making 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 18 shows for an increasing κ_h.

Figure 2.18: IRFs of the employment ratio for different H-vacancy creation cost, κ_h



Only skill-intensity heterogeneity in commodity production

Now we turn to the case in which there are not SAM asymmetries, so we can focus in how are labor market outcome gaps affected by a commodity price shock when the skill-intensity in commodity production changes. Specifically, we will revise the case in which the skill-intensity for high-skilled workers increases. With high-skill intensity in commodity production increasing, basically we are saying that the elasticity of high-skilled labor in commodity production is higher and then this kind of workers yields 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)[27]. The assumption is basically that, in our framework, $\alpha_h > 0.32$, which is the benchmark value. This statement is somewhat related to the Dutch Disease literature, which often assumes the manufacturing tradable sector concentrates learning-by-doing, increasing returns to scale, spillover effects, or other positive externalities (van Wijnbergen (1984)[46]; Lama and Medina (2018)[33], García-Cicco and Kawamura (2015)[25]). Though not exactly the same case for the commodity sector, we can relate a high skill-intensity in commodity production to the case where there are capital-skill complementarities in production.

Figure 2.19: IRFs of the employment ratio for different H-skill intensity in commodity production, α_h

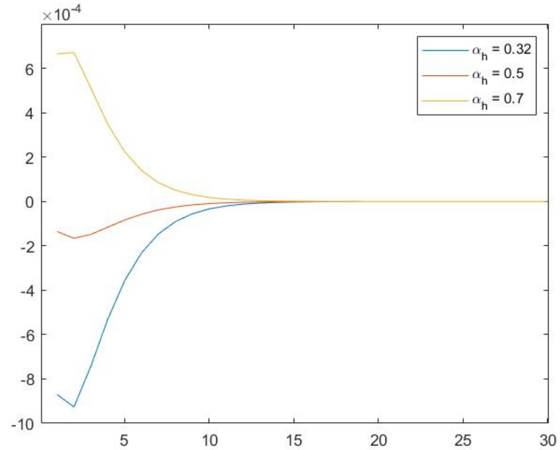


Figure 19 shows the dynamics for the employment ratio when increasing the skill-intensity in commodity production. As the high-skilled elasticity in commodity production increases, firms are more willing to hire high-skilled worker. In other words, the value of high-skilled employment increases as α_h 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 lower employment ratio between workers of different skills.

Finally, Figure 20 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 $\alpha_h = 0.32$ we go back to the neoclassical result where the employment ratio and the wage premium respond in the same direction to a commodity price shock. This is due the fact that workers are homogeneous in their SAM frictions, but the skill-intensity parameter favors ℓ-workers' relative employment and, therefore, their wages. In other words, if different workers face the same labor market institutions, the only important feature driving labor market outcome gaps is the demand channel, which is driven by the skill-intensity in production in our case. Also, it can be readily seen that increasing α_h favors high-skilled workers wages, where the higher α_h is, the higher is the effect of a commodity price shock on impact. The effect is not negligible, since increasing α_h from 0.5 to 0.7 implies an increase of the wage premium IRF on impact of almost twice as much, going from a bit higher than 0.15 to approximately 0.35.

Figure 2.20: IRFs of the wage premium for different H-skill intensity in commodity production, α_h

wp_alphah2.jpg

Summarizing, the results of this section helped us to understand better the shock transmission mechanism that underlies in our model. First, analyzing the case that implies only SAM asymmetries we learned 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, we have that the wage premium decreases because the particular production technology that we 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 6.1.2 we 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.

2.7.4 Wage Decomposition

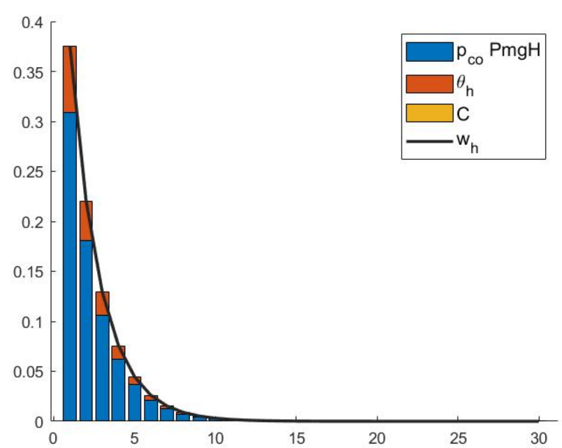
In this section we perform a wage decomposition exercise in order to understand which elements of the workers' wages contribute the most to the wage dynamics when there is a commodity price shock. Let us recall that the wage equation for a k-skilled worker is defined by

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

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, we will consider in the analysis the joint effect of $p_t^{co} PMg_t^k$ on wage dynamics.

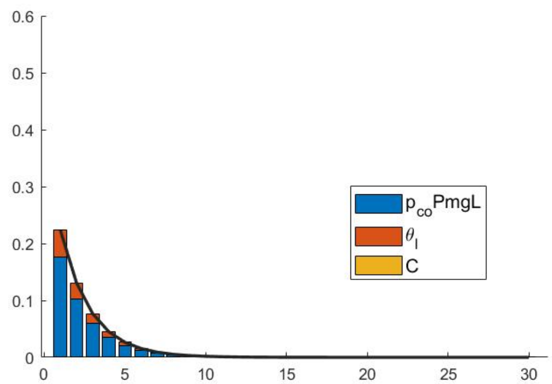
Figures 21 and 22 show the wage decomposition by worker skill type. Starting with Figure 21, it shows the high-skilled workers wage decomposition. It can be seen that the dynamics for w_t^h are mainly decomposed into two components, $p_t^{co} PMg_t^h$ and θ_h. Here, the most important part for the wage 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)[18], where it is documented that the wage decomposition dynamics that arise from a monetary shock come from changes in the firm's surplus.

Figure 2.21: IRF decomposition for w_t^h



Regarding Figure 22, 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 2.22: IRF decomposition for w_t^ℓ



Finally, Figure 23 shows the decomposition for the wage premium dynamics. Again, as in Figures 21 and 22, 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)[18], 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)[18] we have here that the impulse in labor market tightness is higher for high-skilled workers than for low-skilled workers. This means that it seems that, for our case, tighter labor markets contribute to increase the wage premium rather to mitigate it, as in Dolado et al. (2021)[18].

Figure 2.23: IRF decomposition for the wage premium

wp_desagregado.jpg

2.8 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, we have built a SOE-DSGE 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. Our 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. Our findings show that as skill-intensity in the commodity production falls which, in our 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. We have to highlight here that we 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 our calibrated skill-intensity in commodity production. As Dolado et al. (2021)[18] 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 we have 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 us 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, we add to these evidence with recent data and that covers a longer time span.

Overall, the model reproduces well the findings in the SVAR analysis. Nevertheless, the theoretical model that we proposed is simple, and it can be easily extended in a richer Neo-Keynesian framework, which would allow other channels to act, as the exchange rate channel would do. Also, as in Dolado et al. (2021)[18], our 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. We let these features to further research.

Bibliography

[1] M. Abbritti and A. Consolo. Labour market skills, endogenous productivity and business cycles. 2022.

[2] E. Albagli, M. Canales, M. Tapia, and J. Wlasiuk. Understanding the job ladder: The role of tenure and job transitions. *Mimeo. Banco Central de Chile*, 2018.

[3] R. Álvarez Espinoza, Á. García Marín, and S. Ilabaca. Commodity prices shocks and poverty reduction in chile. 2017.

[4] D. Andolfatto. Business cycles and labor-market search. *The american economic review*, pages 112–132, 1996.

[5] R. Barnichon and A. Figura. Labor market heterogeneity and the aggregate matching function. *American Economic Journal: Macroeconomics*, 7(4): 222–49, 2015.

[6] F. Benguria, F. Saffie, and S. Urzúa. The transmission of commodity price super-cycles. Technical report, National Bureau of Economic Research, 2018.

[7] M. Bodenstein, C. J. Erceg, and L. Guerrieri. The effects of foreign shocks when interest rates are at zero. *Canadian Journal of Economics/Revue canadienne d'économique*, 50(3):660–684, 2017.

[8] C. Bosler, N. Petrosky-Nadeau, et al. Job-to-job transitions in an evolving labor market. *FRBSF Economic Letter*, 34, 2016.

[9] E. Boz, C. B. Durdu, and N. Li. Labor market search in emerging economies. *International Finance Discussion Paper*, (989), 2009.

[10] P. Cahuc, F. Postel-Vinay, and J.-M. Robin. Wage bargaining with on-the-job search: Theory and evidence. *Econometrica*, 74(2):323–364, 2006.

[11] A. Campolmi and E. Faia. Labor market institutions and inflation volatility in the euro area. *Journal of Economic Dynamics and Control*, 35(5):793–812, 2011.

[12] A. Caplin, V. Gregory, S. Leth-Petersen, J. Sæverud, C. Tonetti, and G. Violante. Accounting for job-to-job moves: Wages versus values. *Working paper*, 2020.

[13] O. Causa, N. Luu, and M. Abendschein. Labour market transitions across oecd countries: Stylised facts. 2021.

[14] L. J. Christiano, M. Trabandt, and K. Walentin. Introducing financial frictions and unemployment into a small open economy model. *Journal of Economic Dynamics and Control*, 35(12):1999–2041, 2011.

[15] H. Connolly and P. Gottschalk. Wage cuts as investment in future wage growth. *Labour*, 22(1):1–22, 2008.

[16] G. Cruz and T. Rau. The effects of equal pay laws on firm pay premiums: Evidence from chile. *Labour Economics*, 2022.

[17] J. Dinardo, N. Fortin, and T. Lemieux. Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *NBER working paper*, 1995.

[18] J. J. Dolado, G. Motyovszki, and E. Pappa. Monetary policy and inequality under labor market frictions and capital-skill complementarity. *American Economic Journal: Macroeconomics*, 13(2):292–332, 2021.

[19] F. E. Dube, A and M. Reich. Employee replacement costs. *IRLE Working Paper No. 201-10*, 2010.

[20] Z. Eckstein, S. Ge, and B. Petrongolo. Job and wage mobility with minimum wages and imperfect compliance. *Journal of Applied Econometrics*, 26(4):580–612, 2011.

[21] J. Eeckhout and P. Kircher. Assortative matching with large firms. *Econometrica*, 86(1):85–132, 2018.

[22] M. W. Elsby, B. Hobijn, and A. Şahin. The decline of the us labor share. *Brookings Papers on Economic Activity*, 2013(2):1–63, 2013.

[23] A. Fernández, A. González, and D. Rodriguez. Sharing a ride on the commodities roller coaster: Common factors in business cycles of emerging economies. *Journal of International Economics*, 111:99–121, 2018.

[24] J. Fornero, M. Kirchner, and A. Yany. *Terms of trade shocks and investment in commodity-exporting economies*. Banco Central de Chile, 2014.

[25] J. García-Cicco and E. Kawamura. Dealing with the dutch disease: Fiscal rules and macro-prudential policies. *Journal of International Money and Finance*, 55:205–239, 2015.

[26] J. Guerra-Salas, M. Kirchner, and R. Tranamil-Vidal. Search frictions and the business cycle in a small open economy dsge model. *Review of Economic Dynamics*, 39:258–279, 2021.

[27] J. F. Guerra-Salas. Latin america's declining skill premium: a macroeconomic analysis. *Economic Inquiry*, 56(1):620–636, 2018.

[28] J.-O. Hairault. Labor-market search and international business cycles. *Review of Economic Dynamics*, 5(3):535–558, 2002.

[29] R. E. Hall. High discounts and high unemployment. *American Economic Review*, 107(2):305–330, 2017.

[30] Z. Jakab and I. Kónya. An open economy dsge model with search-and-matching frictions: the case of hungary. *Emerging Markets Finance and Trade*, 52(7):1606–1626, 2016.

[31] D. Jinkins and A. Morin. Job-to-job transitions, sorting, and wage growth. *Labour Economics*, 55:300–327, 2017.

[32] I. Jones, A. Naudon, et al. Dinámica laboral y evolución del desempleo en chile. *Economía chilena, vol. 12, no. 3*, 2009.

[33] R. Lama and J. P. Medina. Is exchange rate stabilization an appropriate cure for the dutch disease? *28th issue (March 2011) of the International Journal of Central Banking*, 2018.

[34] S. Leduc, Z. Liu, et al. Robots or workers?: A macro analysis of automation and labor markets. Federal Reserve Bank of San Francisco, 2019.

[35] C. Lizama and B. Villena. Avoiding layoffs: On-the job search and self-insurance. *Working paper*, 2019.

[36] J. P. Medina and C. Soto. Commodity prices and fiscal policy in a commodity exporting economy. *Economic Modelling*, 59:335–351, 2016.

[37] M. Merz. Search in the labor market and the real business cycle. *Journal of monetary Economics*, 36(2):269–300, 1995.

[38] G. Moscarini and F. Postel-Vinay. The cyclical job ladder. *Annual Review of Economics*, 2018.

[39] A. Pellandra. The commodity price boom and regional workers in chile: a natural resources blessing? *Unpublished manuscript*, 2015.

[40] F. Postel-Vinay and J.-M. Robin. Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica*, 2002.

[41] K. Sehnbruch, R. Carranza, et al. *The Chilean system of unemployment insurance savings accounts.* Univ. de Chile, Department de Economía, 2015.

[42] R. Shimer. The cyclical behavior of equilibrium unemployment and vacancies. *American economic review*, 95(1):25–49, 2005.

[43] I. Sorkin. Ranking firms using revealed preference. *The quarterly journal of economics*, 2018.

[44] V. Tjaden and F. Wellschmied. Quantifying the contribution of search to wage inequality. *American Economic Journal: Macroeconomics*, 6(1): 134–61, 2014.

[45] R. Topel and M. Ward. Job mobility and the careers of young men. 107 (2):439–479, 1992.

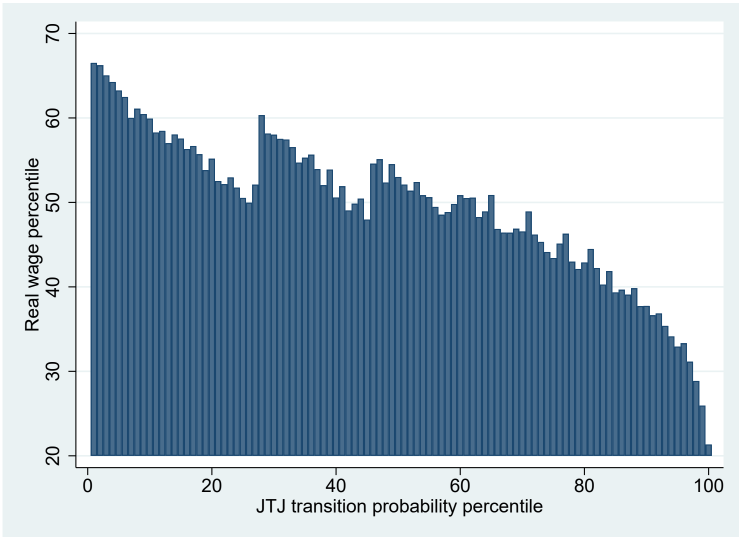
[46] S. Van Wijnbergen. Thedutch disease': a disease after all? *The economic journal*, 94(373):41–55, 1984.

[47] E. L. Wolcott. Employment inequality: Why do the low-skilled work less now? *Journal of Monetary Economics*, 118:161–177, 2021.

A Appendix to Chapter 1

A.1 Other facts

Figure 24: Average real wage percentile by JTJ transition prob percentile



Source: Author's calculations using the UI registry database.

Figure 25: 6-month wage growth by accepted wage percentile (w/o outliers)

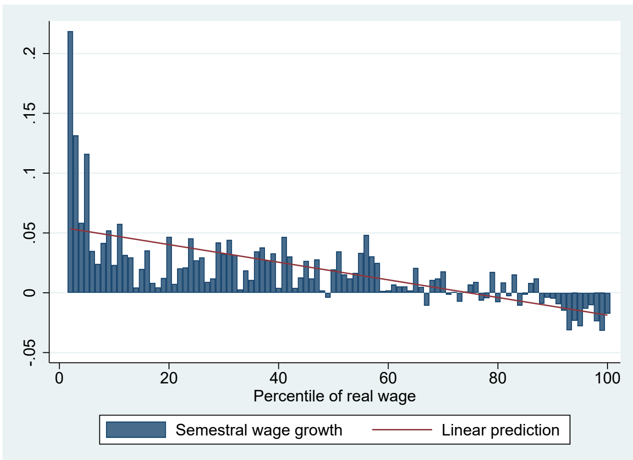
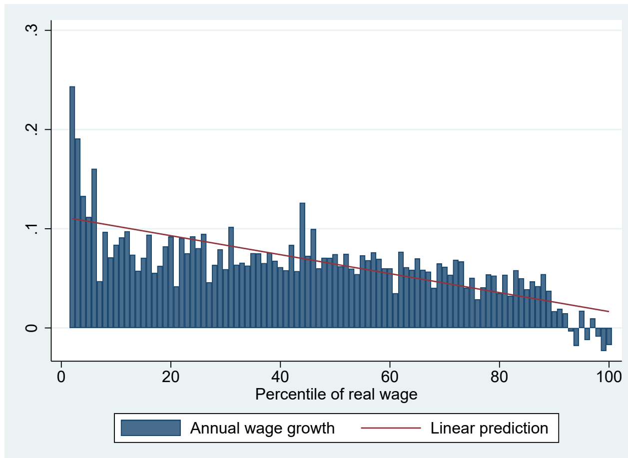


Figure 26: Annual wage growth by accepted wage percentile (w/o outliers)



A.2 Robustness checks results

A.3 DFL

Table 4: JTJ transition and ex-post real wage growth (DFL, 1996)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$JTJ_{i,t}$	0.0053***	0.0064***	0.016***
Num. Obs	12,347,896	10,233,520	7,354,604
Num. Workers	274,010	246,924	200,709
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007).

Table 5: Characterization of JTJ transitions between origin and destination firm variables (DFL, 1996).

	$\Delta log(w_{i,j,t+3})$	$\Delta log(w_{i,j,t+6})$	$\Delta log(w_{i,j,t+12})$
wc_t	0.062***	0.063***	0.052***
$log(w_{i,h,t-1})$	-0.045***	-0.067***	-0.12***
$log(\overline{w}_{h,t-1})$	0.004	-0.003	0.012
$log(\sigma(w_{h,t-1}))$	-0.003	0.004	0.0001
$Age_{h,t-1}$	0.0001	0	0
Num. Obs	51,249	41,289	28,134
Num. Workers	41,827	34,746	24,700
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes:

Table 6: Origin firm's salary and wage cut probability (DFL, 1996).

	$wc_{i,t}$		
	(i)	(ii)	(iii)
$log(w_{i,h,t-3})$	0.13***	0.144***	0.18***
$log(\overline{w}_{h,t-1})$	-	-0.01	0.02
$log(\sigma(w_{h,t-1}))$	-	0.002	0.007
$Age_{h,t-1}$	-	-0.0002**	0
Num. Obs	67,200	61,063	61,063
Num. Workers	51,186	46,979	46,979
Year dummies	No	No	Yes
Month dummies	No	No	Yes
Workers dummies	No	No	Yes

A.4 Truncating age $\leq$ 55

Table 7: Mean values for ex-post real wage growth: JTJ v/s stayers

	$\Delta log(w_{i,t+3})$ (1)	$\Delta log(w_{i,t+3})$ ($wc_{i,t}=1$) (2)	$\Delta log(w_{i,t+3})$ (stayers) (3)
Mean	-0.01	0.022	0.001
	$\Delta log(w_{i,t+6})$ (1)	$\Delta log(w_{i,t+6})$ ($wc_{i,t}=1$) (2)	$\Delta log(w_{i,t+6})$ (stayers) (3)
Mean	0.015	0.049	0.015
	$\Delta log(w_{i,t+12})$ (1)	$\Delta log(w_{i,t+12})$ ($wc_{i,t}=1$) (2)	$\Delta log(w_{i,t+12})$ (stayers) (3)
Mean	0.059	0.097	0.042

Table 8: JTJ transition and ex-post real wage growth ($age \leq 55$)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$JTJ_{i,t}$	0.005***	0.0058***	0.016***
Num. Obs	11,528,692	9,517,383	6,789,794
Num. Workers	263,294	236,643	190,970
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007).

Table 9: Characterization of JTJ transitions between origin and destination firm variables ($age \leq 55$).

	$\Delta log(w_{i,j,t+3})$	$\Delta log(w_{i,j,t+6})$	$\Delta log(w_{i,j,t+12})$
wc_t	0.067***	0.063***	0.088***
$log(w_{i,h,t-1})$	-0.033***	-0.046***	-0.12***
$log(\overline{w}_{h,t-1})$	0.01	0.003	0.004
$log(\sigma(w_{h,t-1}))$	-0.0001	0.001	0.0006
$Age_{h,t-1}$	0.0001*	0	0.0003**
Num. Obs	48,804	39,203	26,562
Num. Workers	39,907	33,056	23,375
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes:

Table 10: Origin firm's salary and wage cut probability ($age \leq 55$).

	$wc_{i,t}$		
	(i)	(ii)	(iii)
$log(w_{i,h,t-3})$	0.13***	0.144***	0.18***
$log(\overline{w}_{h,t-1})$	-	-0.01	0.02
$log(\sigma(w_{h,t-1}))$	-	0.002	0.007
$Age_{h,t-1}$	-	-0.0002**	0
Num. Obs	67,200	61,063	61,063
Num. Workers	51,186	46,979	46,979
Year dummies	No	No	Yes
Month dummies	No	No	Yes
Workers dummies	No	No	Yes

Wage growth trends prior to JTJ transitions

Table 11: Ex-ante real wage growth and JTJ transitions

	$JTJ_{i,t}$	$JTJ_{i,t}$	$JTJ_{i,t}$
$\Delta log(w_{i,t-3})$	-0.007***	-	-
$\Delta log(w_{i,t-6})$	-	-0.0055***	-
$\Delta log(w_{i,t-12})$	-	-	-0.004***
Num. Obs	13,835,091	11,753,410	8,487,361
Num. Workers	292,994	271,528	224,654
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007).

A.5 Checking for heterogeneous effects

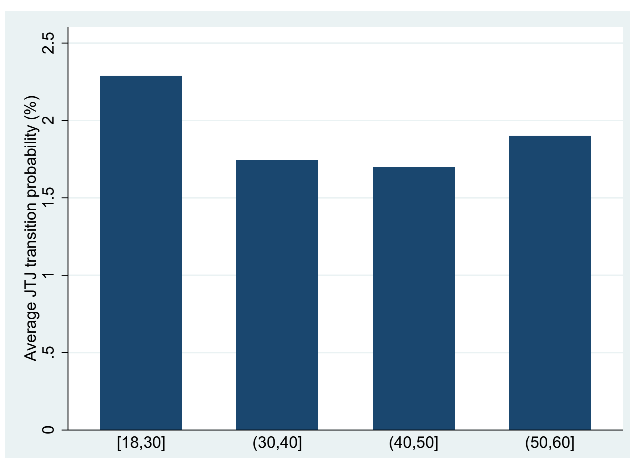
It can be expected that JTJ transition decisions are determined by different conditions that workers may have during their working life. In this section we explore how JTJ transitions and wage growth rates are determined by workers' life-cycle stage and the economic sector which they belong.

By life-cycle

It is intuitive to think that workers' in different stages of the life-cycle take different decisions regarding to accept a new job offer or not, and also how does this decision affect their ex-post outcomes, that is, the wage growth path after they decide whether to stay in their current firm or to move to another by doing a JTJ transition. For example, younger individuals that are starting their working lives are expected to present rather flatter consumption habits and to be free of family duties, which allow them to rotate from one job to another more fluently than older workers which may be attached to financial obligations (e.g., mortgages, and other kind of binding loans) that force them to keep their current jobs and to have a stable income stream in order to avoid falling into debt and being able to smooth consumption. The latter imposes those workers to only accept a job offer that is good enough to be financially solvent and, therefore, not willing to accept any kind of offer as younger workers may do. Bosler and Petrosky-Nadeau (2016)[8] explain this phenomena stating that early in life, the mobility of a fluid labor market allows people to experiment and discover their skills and desired careers. Later in life, when people aremore established in their careers, mobility reflects the opportunity to find better employment and wage gains or to develop new skills at different tasks. Job-to-job transitions occur more frequently earlier in life.

Figure 27 displays the JTJ transition rates across the life cycle. The figure shows that mobility rates are higher for younger workers, where the younger group (18 to 30 years old) have a JTJ transition rate of 2.3%. Mobility rates decline for older workers under 2%. This fact is consistent with the evidence found by Bosler and Petrosky-Nadeau (2016)[8] using the data available from the Census Bureau's Survey of Income and Program Participation (SIPP) for the United States.

Figure 27: JTJ transition probability by age group.



In the same spirit of the prior analysis, is to be expected that wage growth patterns work differently in different stages of the life cycle. To study this, tables 12 to 15 display the results of the estimation of equation (1.4) by restricting it to four different age groups: (i) 18 to 30 y/o; (ii) 31 to 40 y/o; (iii) 41 to 50 y/o and, (iv) 51 to 60 y/o. Generally speaking, at every stage of the life cycle there is a positive correlation between doing a JTJ mobility and wage growth. Besides, the effects seem to be stronger at early stages of life. This pattern does not hold for older workers (51 to 60 y/o) where the relation is statistically significant only for yearly wage growth. The latter suggests that older workers that move JTJ do not experience higher wage growth rates than their peers that choose to stay in their current firms.

Table 12: JTJ transitions and ex-post real wage growth (age: 18-30)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$JTJ_{i,t}$	0.008***	0.009***	0.02***
Num. Obs	2,806,340	2,226,678	1,495,274
Num. Workers	117,753	101,468	74,999
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Table 13: JTJ transitions and ex-post real wage growth (age: 31-40)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$JTJ_{i,t}$	0.006***	0.008***	0.014***
Num. Obs	3,990,992	3,315,962	2,394,158
Num. Workers	125,604	113,215	89,495
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Table 14: JTJ transitions and ex-post real wage growth (age: 41-50)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$JTJ_{i,t}$	0.006***	0.005**	0.015***
Num. Obs	3,493,638	2,967,951	2,221,428
Num. Workers	102,535	93,549	75,768
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Table 15: JTJ transitions and ex-post real wage growth (age: 51-60)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$JTJ_{i,t}$	0.003	0.004	0.017***
Num. Obs	2,105,666	1,763,913	1,272,985
Num. Workers	63,195	57,236	44,788
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

It is also relevant to check whether there are life cycle effects for accepting a wage cut regarding ex-post wage growth when workers move job-to-job. Tables 16 to 19 display the results for the estimation of equation (1.5) for the different age groups stated above. The tables show that accepting wage cuts is positively related with ex-post wage growth for every age group. The only exception is for the older group of workers (51 to 60 y/o) when the outcome variable is the 6-month wage growth rate, where there is no statistically significant difference between wage growth rates for wage cut takers and non-takers. Regarding the magnitude of the correlation for workers in the 18 to 30 y/o range wage cut takers experience growth rates between 8.2% and 9% higher than non-takers; for workers between 31 to 40 y/o the rates are between 3.4% and 6%; for workers between 41 to 50 y/o the rates are between 7% and 12%, and for workers between 51 to 60 y/o the rates are between 0% and 6%. This evidence suggests that, when moving JTJ, wage cuts are positively related with wage growth rates despite of the stage of the life cycle that movers are in.

Table 16: Wage cuts and ex-post wage growth rate (age: 18-30)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$wc_{i,t}$	0.09***	0.085***	0.082***
$log(w_{i,t-1})$	-0.081***	-0.044*	-0.22***
$log(\overline{w}_{j,t-1})$	0.023	0.008	0.017
$log(\sigma(w_{j,t-1}))$	0.017	0.004	0.022
$Age_{j,t-1}$	0.0001	-0.0003	0.001**
Num. Obs	13,838	10,707	6,931
Num. Workers	12,180	9,674	6,445
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Table 17: Wage cuts and ex-post wage growth rate (age: 31-40)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$wc_{i,t}$	0.06***	0.034***	0.06***
$log(w_{i,t-1})$	-0.03*	-0.04***	-0.12***
$log(\overline{w}_{j,t-1})$	0.012	-0.0003	0.05
$log(\sigma(w_{j,t-1}))$	-0.004	-0.012	-0.03
$Age_{j,t-1}$	0.0001	0.0002	0.0004*
Num. Obs	17,607	14,337	9,857
Num. Workers	15,163	12,672	9,039
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Table 18: Wage cuts and ex-post wage growth rate (age: 41-50)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$wc_{i,t}$	0.07***	0.09***	0.12***
$log(w_{i,t-1})$	-0.03*	-0.07***	-0.1***
$log(\overline{w}_{j,t-1})$	-0.03*	-0.02	-0.05
$log(\sigma(w_{j,t-1}))$	0.003	0.01	0.018
$Age_{j,t-1}$	0.0001	-0.0002	0.0002
Num. Obs	13,136	10,792	7,608
Num. Workers	11,367	9,560	6,985
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

Table 19: Wage cuts and ex-post wage growth rate (age: 51-60)

	$\Delta log(w_{i,t+3})$	$\Delta log(w_{i,t+6})$	$\Delta log(w_{i,t+12})$
$wc_{i,t}$	0.06***	0.03	0.05**
$log(w_{i,t-1})$	-0.02	0.002	-0.06
$log(\overline{w}_{j,t-1})$	0.05	0.02	0.05
$log(\sigma(w_{j,t-1}))$	-0.04**	-0.02	-0.01
$Age_{j,t-1}$	-0.0001	-0.0003	0.0001
Num. Obs	6,835	5,585	3,837
Num. Workers	5,984	5,013	3,558
Year dummies	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Workers dummies	Yes	Yes	Yes

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

By industry

The economic sector that workers belong may also have an influence in their transition outcomes. For example, job mobility may be higher in some sectors than others, and also the wage ladder may be heterogeneous between sectors, which may affect workers' decision of accepting a wage cut when a job offer arrives depending the sector of that offer. Table 20 summarizes the industry disaggregated average job transition probability and wage cut probability for my sample. Here, I took the first eighteen chilean economic sectors according to the International standard industrial classification of all economic activities

(ISIC). Regarding transition probability, the table shows that it ranges from 2% to 4.2%, where the former corresponds to the electricity supply sector, while the latter to the construction sector. Other sectors with high relative job mobility are agriculture (3.2%), hotels and tourism (3.4%), public administration (3.7%) and arts and entertainment (3.8%).

Table 20: Ex-ante real wage growth and JTJ transitions

Industry	Observations	$\mathbb{P}(JTJ = 1)$	$\mathbb{P}(wc = 1)$
Agriculture	3,626	3.2%	45.3%
Mining	1,120	2.4%	39%
Manufacturing	6,627	2.7%	41.4%
Electricity supply	344	2%	36.6%
Water supply	328	2.8%	41.7%
Construction	4,953	4.2%	46.7%
Retail	14,823	2.7%	39.8%
Transportation	5,585	2.9%	46.7%
Hotels and Tourism	4,676	3.4%	39.5%
Information and Communications	2,550	2.5%	38.7%
Finance	3,814	2.5%	38.9%
Real estate	1,207	2.9%	44.2%
Scientific and professional activities	5,378	2.9%	42.7%
Administrative services	9,661	3.3%	43.3%
Public administration	356	3.7%	45.5%
Education	4,044	2.3%	48.9%
Health	1,435	2.9%	42.6%
Arts and entertainment	356	3.8%	43.2%

Source: Author's calculations using the UI data registry.

On the other hand, wage cut probability ranges between 36.6% to 48.9%, and the economic sectors associated with these values are electricity supply and education, respectively. In other words, workers that transition coming from a firm in the electricity supply industry have a 36.6% of accepting a new job, and those movers coming from a firm in the education sector have a 48.9% of accepting a wage cut, regardless the economic sector they arrive to in their new job.

It is also interesting to characterize ex-post wage growth patterns by industry. This is important because, as was stated above, wage ladders may differ by economic sector which, at the same time, may condition growth and career opportunities of workers within them. Table 21 summarizes these features displaying the average wage growth by industry 3, 6 and 12 months following a JTJ transition.

Table 21: Ex-post real wage growth by firm sector

Industry	$\Delta log(w_{i,j,t+3})$	$\Delta log(w_{i,j,t+6})$	$\Delta log(w_{i,j,t+12})$
Agriculture	-1.5%	1.8%	4.3%
Mining	2.1%	3.3%	7.5%
Manufacturing	0.02%	1.5%	7.2%
Electricity supply	-0.4%	1.7%	5.1%
Water supply	-1.4%	6.05%	8.2%
Construction	-2.6%	0.4%	5.4%
Retail	-0.5%	1.3%	6.2%
Transportation	-1.5%	0.5%	4.9%
Hotels and Tourism	-1.5%	2.2%	6.7%
Information and Communications	-0.5%	2.8%	6.8%
Finance	0.6%	2.4%	7.04%
Real estate	-0.3%	1.6%	4.1%
Scientific and professional activities	0.1%	1.5%	6.2%
Administrative services	-2.7%	0.5%	4.2%
Public administration	-5.9%	5.5%	11.1%
Education	0.2%	2.5%	5%
Health	0.7%	1.4%	4.5%
Arts and entertainment	-0.4%	-0.8%	6.2%

Notes: .

Another possible source of heterogeneities between economic sectors is how job mobility affects ex-post wage growth rates of workers that arrive to different sectors. To study the latter I estimate equation (1.4) at the industry level in order to compare the wage growth rates of movers and stayers within a particular sector. The goal is to compare wage growth rates of workers arriving to a particular sector with rates of workers that already belong to that sector and stayed in their current jobs. Table 22 summarizes the results of this estimation in which I only considered a 3-month and 12-month wage growth rates for the analysis. The exercise shows that there is a positive correlation between moving JTJ and ex-post wage growth rates for almost every economic sector. The exceptions are: electricity and water supply, public administration, education and, arts and entertainment.

Table 22: Ex-post real wage growth and by firm sector

Industry	$\hat{\beta}$ $(k = 3)$	$\hat{\beta}$ $(k = 12)$
Agriculture	0.013***	0.01*
Mining	0.035***	0.03***
Manufacturing	0.02***	0.03***
Electricity supply	-0.022*	0.005
Water supply	-0.012	0.03
Construction	0.014***	0.02***
Retail	0.016***	0.015***
Transportation	0.01***	0.014***
Hotels and Tourism	0.02***	0.04***
Information and Communications	0.011**	0.017**
Finance	0.014**	0.035***
Real estate	0.033***	0.026*
Scientific and professional activities	0.024***	0.024***
Administrative services	0.003	0.02***
Public administration	-0.002	-0.001
Education	-0.006*	0.001
Health	0.04***	0.013
Arts and entertainment	0.003	0.035

Notes: .

A.6 Characterization of ex-post wage growth patterns by observables

It is reasonable to think that different types of workers will experience different wage growth patterns during their working life cycle. For example, workers with different educational levels are allowed to work in different types of jobs which, at the same time, will be associated with different wage ladders, with variation in the wage cap and the wage growth rates. This same argument applies when comparing workers of different gender, marital status, or age. In the main body of this article the econometric estimations included fixed effects in order to take advantage of the panel structure of the data. Therefore, as gender, educational level, age and marital status, exhibit little (or none) variation at a monthly level, all these features were included in the fixed effect of the corresponding equations. In order to understand how do the latter observable features determine ex-post wage growth rates, I estimate the following equation

$$\Delta log(w_{i,t+k}) = \beta_0 + \boldsymbol{\beta}_1 \boldsymbol{Y}_{i,t} + \varepsilon_{i,t}, \text{ for } k \in \{3, 6, 12\}, \tag{43}$$

where $\boldsymbol{Y}_{i,t}$ is a vector containing dummy variables for gender (male = 1) and marital status (married = 1), a categorical variable for educational level, and age. This equation is estimated under two specifications: (i) every JTJ mover in period t and, (ii) conditioning on JTJ movers that accept a wage cut.

The results of both specifications are summarized in Table 23 in panel A and B, respectively.

Table 23: Ex-post wage growth determinants by workers' observable features.

	Panel A: Unconditional		
	$\Delta log(w_{i,j,t+3})$	$\Delta log(w_{i,j,t+6})$	$\Delta log(w_{i,j,t+12})$
$Male_i$	-0.01***	-0.005**	-0.012***
$Married_i$	0.0007	0.004*	0.01**
$Educational\ level_i$	0.002***	0.0005	-0.0008
Age_i	0.0004***	-0.0001	-0.001***
Num. Obs	70,591	55,074	36,351
	Panel B: Conditional in $wc_{i,t} = 1$		
	$\Delta log(w_{i,j,t+3})$	$\Delta log(w_{i,j,t+6})$	$\Delta log(w_{i,j,t+12})$
$Male_i$	-0.02***	-0.01**	-0.01**
$Married_i$	0.003	0.002	0.003
$Educational\ level_i$	0.002***	0.0006	-0.0001
Age_i	0.0001	-0.0002	-0.0001***
Num. Obs	32,735	24,689	15,963

Notes: Wages are deflated by the CPI (base January 2007). *** means $p-value < 0.01$. ** means $p-value < 0.05$. * means $p-value < 0.1$.

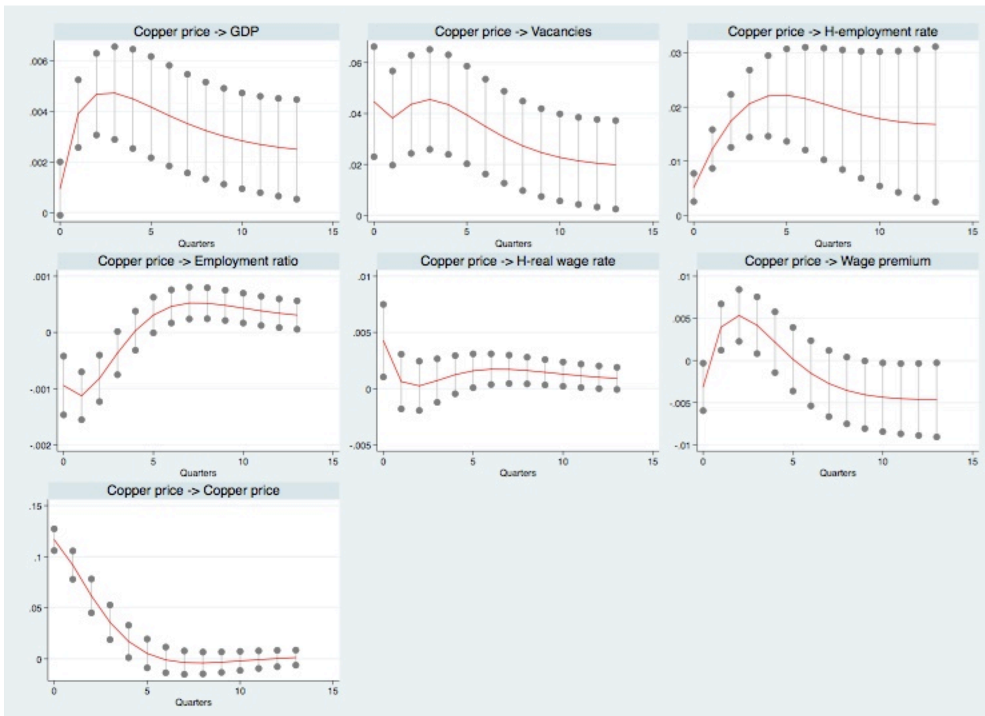
Panel A of Table 23 shows that when considering every JTJ mover, women experience between 0.5% and 1.2% higher wage growth rates than men; being married is associated with wage growth rates in the range of 0.04 and 1% higher than non-married workers, but only statistically significant for yearly rates; completing an additional educational level yields 0.2% higher quarterly wage growth rates and, older workers exhibit 0.04% higher quarterly wage growth rates but 0.1% lower yearly growth rates.

When conditioning on workers that accept a wage cut, panel B shows that the patterns are almost the same regarding the unconditional sample, with the difference that there are no significant effects of being married for any ex-post wage growth definition and that there are not significant differences for older workers in quarterly wage growth rates.

B Appendix to Chapter 2

B.1 Tables and plots

Figure 28: 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 29: Representative household allocation of labor between productive sectors.

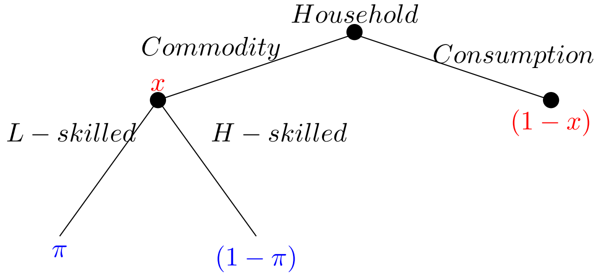


Figure 30: Share of Copper Workers en Chile, 2014-2020

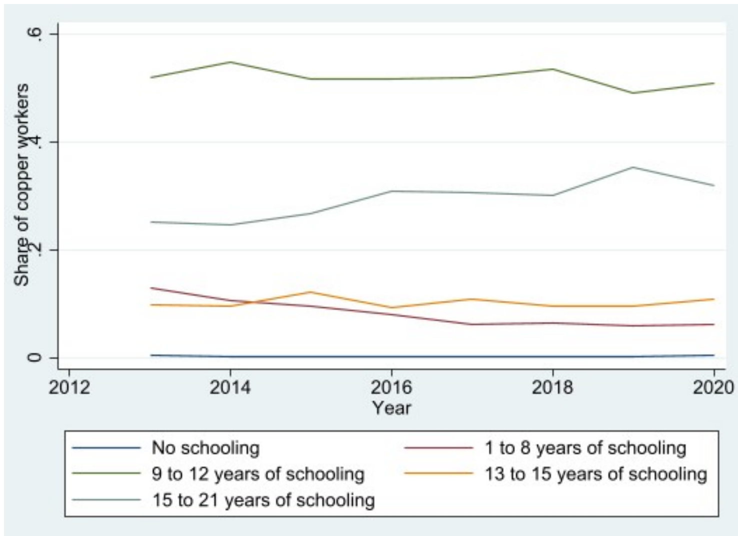


Figure 31: Source: Encuesta Nacional de Empleo (ENE). Instituto Nacional de Estadísticas

B.2 Equilibrium conditions (non-linear)

$$1 = \beta\,\mathbb{E}_t\left[\theta_{t+1}\,\frac{c_t}{c_{t+1}}\,r_t\right] \tag{44}$$

$$r_t = a + zr_t + \psi\,(\exp(D_t - D\_ss) - 1) \tag{45}$$

$$m_t^\ell = (u_t^\ell)^\alpha\,(v_t^\ell)^{(1-\alpha)} \tag{46}$$

$$q_t^\ell = \frac{m_t^\ell}{v_t^\ell} \tag{47}$$

$$N_t^\ell = m_{t-1}^\ell + (1-\delta_t)\,N_{t-1}^\ell \tag{48}$$

$$u_t^\ell = \pi\,x - (1-\delta_t)\,N_{t-1}^\ell \tag{49}$$

$$U_t^\ell = \pi\,x - N_t^\ell \tag{50}$$

$$m_t^h = \mu^h\,(u_t^h)^\alpha\,(v_t^h)^{(1-\alpha)} \tag{51}$$

$$q_t^h = \frac{m_t^h}{v_t^h} \tag{52}$$

$$N_t^h = m_{t-1}^h + (1-\delta_t)\ N_{t-1}^h \tag{53}$$

$$u_t^h = x\ (1-\pi) - (1-\delta_t)\ N_{t-1}^h \tag{54}$$

$$U_t^h = x\ (1-\pi) - N_t^h \tag{55}$$

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

$$\eta_t^\ell = \frac{v_t^\ell}{u_t^\ell} \tag{57}$$

$$\frac{\kappa_h}{q_t^h} = \beta\,\mathbb{E}_t\left[\frac{\theta_{t+1}\,c_t}{c_{t+1}}\ (1-\delta_{t+1})\ \left(\frac{\alpha_h\,p_{t+1}^{co}\,Y_{t+1}^{co}}{N_{t+1}^h} - w_{t+1}^h + \frac{\kappa_h}{q_{t+1}^h}\right)\right] \tag{58}$$

$$\frac{\kappa_\ell}{q_t^\ell} = \beta\,\mathbb{E}_t\left[\frac{\theta_{t+1}\,c_t}{c_{t+1}}\ (1-\delta_{t+1})\ \left(\frac{(1-\alpha_h)\,p_{t+1}^{co}\,Y_{t+1}^{co}}{N^\ell{}_{t+1}} - w_{t+1}^\ell + \frac{\kappa_\ell}{q_{t+1}^\ell}\right)\right] \tag{59}$$

$$Y_t^c = Z_t\ (1-x) \tag{60}$$

$$Y_t^{co} = Z_t\,(HN_t^h)^{\alpha_h}\ (N_t^\ell)^{1-\alpha_h} \tag{61}$$

$$C_t = Y_t^c + \gamma Y_t^{co} \tag{62}$$

$$Y_t = C_t + v_t^h\,\kappa_h + v_t^\ell\,\kappa_\ell + (1-\gamma)p_t^{co}Y_t^{co} \tag{63}$$

$$w_t^h = b_h\ \left(\frac{\alpha_h\,p_{t+1}^{co}\,Y_{t+1}^{co}}{N_{t+1}^h} + \theta_t^h\,\kappa_h\right) + (1-b_h)\ (\phi + \chi_h C_t) \tag{64}$$

$$w_t^\ell = b_\ell\ \left(\frac{(1-\alpha_\ell)\,p_{t+1}^{co}\,Y_{t+1}^{co}}{N_{t+1}^\ell} + \theta_t^\ell\,\kappa_\ell\right) + (1-b_\ell)\ (\phi + \chi_\ell C_t) \tag{65}$$

$$\log(\delta_t) = (1-\rho_\delta)\ \log\left(\bar{\delta}\right) + \rho_\delta\ \log(\delta_{t-1}) + \varepsilon_{\delta t} \tag{66}$$

$$\log(Z_t) = (1-\rho_Z)\ \log\left(\bar{Z}\right) + \rho_Z\ \log(Z_{t-1}) + \varepsilon_{t,Z} \tag{67}$$

$$\log(\theta_t) = \rho_\theta\ \log(\theta_{t-1}) + \varepsilon_{\theta,t} \tag{68}$$

$$\log(p_t^{co}) = (1-\rho_{p^{co}})\log(\bar{p}^{co}) + \rho_{p^{co}}\log(p_{t-1}^{co}) + \varepsilon_{t,p^{co}}, \tag{69}$$

$$\log(z_t^r) = (1-\rho_{zr})\log(\bar{z}^r) + \rho_{zr}\log(z_{t-1}^r) + \varepsilon_{t,zr}. \tag{70}$$

$$emp\_rate_t = N_t^h - N_t^\ell \tag{71}$$

$$wage\_prem_t = w_t^h - w_t^\ell \tag{72}$$