The Impact of Monetary Policy on a Labor Market with Heterogeneous Workers: The Case of Chile

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May 26, 2017

Abstract

We use a factor-augmented vector autoregressive (FAVAR) model to analyze the effect of a contractionary monetary shock on macroeconomic aggregates and labor market indicators for different demographic groups in Chile classified by industry, age, and income quintile. We find that for most groups the job-separation rate and idiosyncratic earnings volatility increase after interest rate rise. The response of the job-finding rate is more mixed with decreases in some groups and an increase for others after an interest rate shock. The labor market in the primary sector is the least sensitive to monetary shocks.

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1 Introduction

The economic effects of monetary policy have been broadly studied using different empirical and theoretical approaches, with most studies showing that monetary shocks have a real effect on output and that inflation responds negatively to a contractionary monetary policy shock (Christiano et al., 1999). Furthermore, recent empirical studies for the United States show that the welfare costs of recessions are significantly larger if one accounts for job displacement risk (Krebs, 2003, 2007) and its heterogeneous impact on different agents (De Santis, 2007). Wage volatility in the United States is counter-cyclical (Storesletten et al., 2001, 2004), especially among workers experiencing unemployment spells (McKay and Papp, 2011). Households face substantially larger earnings shocks during recessions (Storesletten et al., 2001, 2004; McKay and Papp, 2011; Davis and von Wachter, 2011; Guvenen et al., 2014), and these earnings losses are highly persistent (Davis and von Wachter, 2011).

In this study we examine how different groups of workers in Chile react to the business cycle and to changes in monetary policy. We analyze the effect of a contractionary monetary shock on the job-finding and separation rates, wage volatility, and labor productivity of different groups of workers. Specifically, we classify workers into 45 distinct groups by (a) economic sector (primary, secondary, tertiary), (b) age (16–35, 36–54, and 55 or older), and (c) income quintile (with lowest income being quintile 1 and highest income being quintile 5). We then estimate a factor-augmented vector autoregressive (FAVAR) model to analyze the transmission effect of a contractionary monetary shock on the labor market experiences of the different Chilean demographic groups.

The FAVAR impulse–response functions show that the job-separation rate and wage volatility tend to increase after a contractionary monetary shock. However, economic sectors in the economy react in different ways. The secondary sector shows a significant reaction in terms of an increase in both the job-separation rate and the idiosyncratic wage volatility. The job-finding rate has a mixed response to an increase in the interest rate, although for some demographic groups in the secondary and tertiary sectors the job-finding rate does fall significantly after a contractionary monetary shock. Overall, the primary sector reacts less both in terms of employment flows, whether as job separation or creation, and in terms of wage volatility.

To measure the labor market experiences of different Chilean workers, we use a rich data set constructed by Madeira (2015). Using the National Employment Survey, which covers a sample of 35,000 households at a quarterly frequency, Madeira (2015) estimated the job-separation rate (the probability that an employed worker will lose his or her job in the next three months), the job-finding rate (the probability that an unemployed worker will find a job within three months), and their wage volatility (the standard deviation of the annual change in labor earnings). The results show that Chile has a fluid labor market (Jones and Naudon, 2009), with unemployment inflow and outflow rates similar to those in the United States and substantially higher than those in other OECD countries (Elsby et al., 2013). Also, the average employed worker faces idiosyncratic income shocks with a standard deviation of 18%, which is roughly similar to estimates for other countries (Krueger et al., 2010).

Relative to previous studies of the business cycle in Chile such as Del Negro and Schorfheide (2008), we innovate by using measures of how monetary policy and the business cycle affect heterogeneous workers and different economic sectors. For instance, ours is the first work to use a measure of real labor productivity growth for each of the three economic sectors in Chile, and we show that productivity growth is strongly correlated for all sectors, which seems to confirm that labor markets in Chile are flexible enough to allow labor flows to equalize labor productivity across different industries. We also find that unemployment, separation and job-finding rates, and wage volatility are heterogeneous across worker types, yet there is a strong cyclical component that affects all groups. Low-income workers experience both higher unemployment rates and wage volatility. However, low-income workers have a higher job-finding rate and therefore face shorter unemployment spells, perhaps because their job matches involve less specific human capital.

In addition to being related to studies of workers' heterogeneous income shocks during the business cycle (Storesletten et al., 2001, 2004), our study relates to the empirical research on the cyclical fluctuations of the labor market (Pappa, 2009; Trigari, 2009; Mumtaz and Zanetti, 2012; Madeira, 2014). Estimating a structural vector autoregressive (SVAR) model, Ravn and Simonelli (2007) concluded that hours worked, employment, vacancies, and the vacancies-unemployment ratio decrease in response to an increase in the federal funds rate. Moreover, labor productivity first declines briefly and then increases after a few quarters. Monetary policy also affects real wages, which seems inconsistent with the high degree of nominal rigidity in the labor market. Using a standard VAR reduced form, Olivei and Tenreyro (2007) found that an expansionary monetary shock increases wages and hours. Moreover, the response of wages is mildly procyclical, whereas hours react more significantly when the shock occurs in the first or second quarter of the calendar year. Peneva (2013) showed that hourly earnings respond positively to an expansionary monetary shock, a response that is similar across both tertiary and goods sectors. Braun et al. (2009) estimated a SVAR model for the United States that includes both demand and supply shocks. They found that an expansionary monetary shock increases vacancies and the job-finding and job-creation rates, whereas it decreases the separation and job-destruction rates. Finally, they concluded that responses induced by supply shocks are more persistent than those induced by demand shocks.

This article is organized as follows. Section 2 summarizes the evolution of the labor productivity, employment flows, and wage volatility for the primary, secondary, and tertiary sectors in Chile over the last 23 years. Section 3 describes the structure of the FAVAR model estimated from the macro variables and the labor market statistics for each of the 45 demographic groups in our data. Finally, Section 4 summarizes the main results, while Section 5 summarizes our conclusions.

2 The evolution of labor markets in Chile

We now describe the evolution of the macroeconomic series and the labor markets in Chile. Table 1 shows that the quarterly CPI growth rate fluctuates between values as low as 0.12% (the 10th percentile for all periods between 1996 and 2012) and values as high as 1.81% (the 90th percentile for all periods). It is worth noting that because these are quarterly values, 1.81% corresponds to an annualized inflation of 7.24%. The median and average quarterly CPI for 1996–2012 is 0.52% and 0.88%, respectively, which are values well within the bands of 2% to 4% for the annual inflation target followed by the Chilean Central Bank. All the economic sectors in Chile have exhibited a robust real productivity growth at average rates between 0.47% and 0.66%.[1] The primary sector was the industry with both the highest mean productivity growth and the most volatile one with rates ranging from as low as −2.71% (the 10th percentile observed for 1996–2012) and as high as 4.45% (the 90th percentile during the same period). Perhaps the secondary sector was the least developed of all the three main economic sectors and, therefore, the one with the largest gains to make. It is also notable that the tertiary sector has much less volatility in real productivity growth than the other sectors, which can be interpreted as the result of the primary and secondary sectors being more subject to international competition and open economy shocks.

Table 1: Distribution of the growth rates (%) of consumer price index and real productivity by percentile. Quarterly data 1996:1–2012:4

Variable (quarterly growth)	Mean	P10	P25	P50	P75	P90
Consumer price index (CPI)	0.88	0.12	0.52	0.80	1.21	1.81
Real productivity all sectors (PRO)	0.61	−1.06	−0.04	0.50	1.65	2.04
Real productivity primary sector (PRO1)	0.66	−2.71	−0.63	0.76	2.33	4.45
Real productivity secondary sector (PRO2)	0.47	−2.22	−0.59	0.50	2.25	3.72
Real productivity tertiary sector (PRO3)	0.62	−0.62	0.09	0.64	1.33	2.05

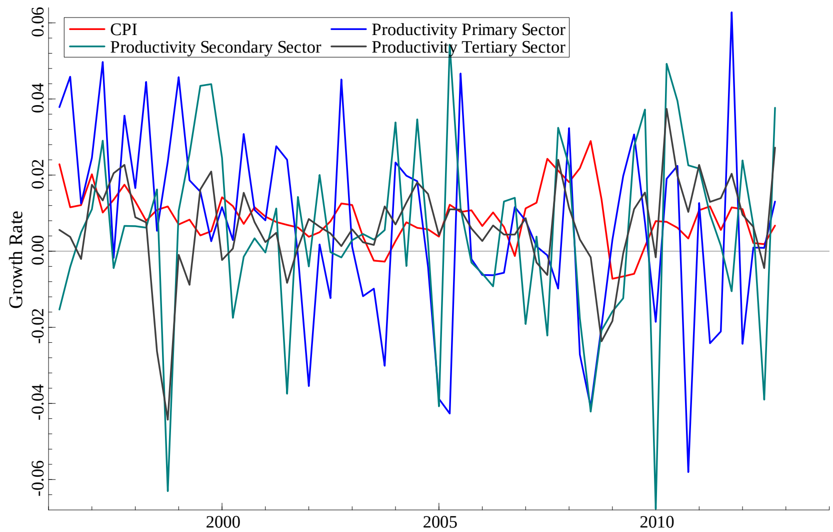
Note 1: Pi, $i = 10, 25, 50, 75, 90$, is the percentile used to classified the growth rate of the variables.

Figure 1 plots the actual evolution of quarterly growth rates of the CPI and the real productivity for each economic sector for 1996–2012. The plot shows that CPI and the real productivity of the three sectors of economic activity are relatively uncorrelated over this period. However, most of the positive and negative spikes in real productivity growth coincide for the primary, secondary, and tertiary sectors, which shows that all labor markets are strongly correlated. This is a sign that labor markets in Chile are integrated across different industries because labor flows would tend to equalize productivity across the different economic sectors.

Table 2 reports the correlation coefficients between each pair of aggregate variables for 1996–2012. We report the correlation both for the variables in their pure form and for their Hodrick-Prescott (HP) cyclical components, which, in a few cases, give different results. In general, CPI fluctuations have a low correlation with real productivity growth. CPI growth is negatively correlated with the unemployment rate and the separation rate but is positively correlated with the job-finding rate. This is evidence for the traditional short-term Phillips curve, with inflation and unemployment correlated negatively (Christiano et al., 1999). The real productivity growth for the labor force has a low correlation with labor market variables such as unemployment, separation, and job-finding rates, which might be interpreted as evidence for short-term rigidity in the Chilean labor market. Wage volatility is positively correlated with the unemployment rate and negatively correlated with the job-

[1] The primary sector in the Chilean economy, which considers agriculture and forestry, fishery, and mining activities, accounted for 14.8% of the real GDP in 2012. The secondary sector, corresponding to the manufacturing industry, represented 10.5% of the real GDP. Finally, the tertiary sector accounted for 66.1% of the real GDP. The percentages do not sum 100 because the real values are calculated using chained volume series that lose the additive property.

Figure 1: Consumer price index (CPI) and real productivity growth by industrial sector. Quarterly data 1996:1–2012:4



finding rate, showing that in Chile idiosyncratic wage risk also increases during recessions in a manner similar to that in the United States (Storesletten et al., 2001, 2004; McKay and Papp, 2011). Both the separation and job-finding rates have a high correlation with unemployment fluctuations, which shows that, as in the case of other countries, both job creation and destruction play a role in unemployment fluctuations (Fujita and Ramey, 2009; Elsby et al., 2013).

In Table 3 we report the same correlation matrix for the HP cyclical components of each of the three economic sectors. Real productivity growth for the primary, secondary, and tertiary sectors is correlated with the overall economy's productivity growth of 54%, 72%, and 89%, respectively. This is strong evidence that labor flows occurs across different economic sectors and that long-term productivities tend to equalize. CPI growth is negatively correlated with the unemployment and separation rates only in the primary and secondary sectors. However, the job-finding rate is positively correlated with CPI growth in the secondary and tertiary sectors. This shows that the primary sector reacts to inflation shocks mostly in terms of job destruction, while the tertiary sector reacts to inflation shocks in terms of job creation. The secondary sector, however, reacts to inflation shocks both in terms of job creation and destruction. In all economic sectors the unemployment and job-separation rates are highly positively correlated, with coefficients between 69% and 82% for each sector, but the correlation of unemployment with the job-finding rate is much lower. This evidence seems to point out that job destruction is responsible for most of the cyclical movement in unemployment in Chile. Wage volatility is high and positively correlated with unemployment fluctuations only in the secondary and tertiary sectors. Therefore, in Chile only in the secondary and tertiary sectors does a simultaneous cycle of both high unemployment and high idiosyncratic wage volatility affect workers.

Finally, Figures 2, 3, and 4 show the evolution of the labor market variables (wage volatility, unemployment, separation, and job-finding rates) for the primary, secondary, and tertiary

Table 2: Correlation coefficients of CPI and real productivity growth with the overall unemployment flows and wage volatility. Quarterly data 1996:1–2012:4

Correlation of standard variables (%)						
	CPI	PRO	U	EU	UE	STDI
Consumer price index (CPI)	100					
Real productivity (PRO)	−2.5	100				
Unemployment rate (U)	−27.3	−12.4	100			
Separation rate (EU)	−19.5	−2.8	55.2	100		
Job-finding rate (UE)	28.7	8.4	−71.2	13.5	100	
Wage volatility (STDI)	−20.8	10.4	38.5	13.1	−34.0	100
Correlation of Hodrick-Prescott cyclical component (%)						
	CPI	PRO	U	EU	UE	STDI
Consumer price index (CPI)	100					
Real productivity (PRO)	−3.7	100				
Unemployment rate (U)	−12.3	3.6	100			
Separation rate (EU)	−14.7	−2.4	71.2	100		
Job-finding rate (UE)	11.3	−14.6	−21.6	45.1	100	
Wage volatility (STDI)	−15.1	15.9	24.6	5.8	−26.2	100

sectors, respectively. For each sector we show the separate evolution for the workers in each national income quintile (with quintile 1 representing the lowest income and 5 the highest). Several facts stand out. First, a significant seasonality exists in the unemployment, separation, and job-finding rates, which is strongest for the primary sector. Second, the shocks affecting all workers have a significant common component because unemployment, job-separation, and job-finding rates tend to move together for all income quintiles. Also, for all economic sectors the unemployment rate is lowest for workers in the income quintiles 4 and 5, with the exception of the secondary sector during the 1990s. Similarly, the highest income workers (quintile 5) show the lowest job-separation rates in all sectors and for all time periods. Finally, in all the economic sectors wage volatility is highest for the bottom income quintile, whereas workers of quintiles 3 and 4 have the lowest idiosyncratic wage volatility. The differences in annual wage volatility are in fact quite substantial, with workers in quintile 1 having a wage volatility around 40% to 50% while the workers in quintiles 3 and 4 have values of just 6% to 12%. Curiously, Figures 2, 3, and 4 show that wage volatility increases during both recessions (such as the 1999 and 2009 economic downturns) and expansions (such as the year 2006).

Table 3: Correlation coefficients of CPI and real productivity growth with unemployment flows and wage volatility by economic sector. Quarterly data 1996:1–2012:4

Sector	Correlation of Hodrick-Prescott cyclical component (%)							
		CPI	PRO	PRO1	U	EU	UE	SDTI
	Consumer price index (CPI)	100						
	Real productivity (PRO)	−3.7	100					
	Productivity primary sector (PRO1)	−11.7	54.3	100				
Primary	Unemployment rate (U)	−12.8	2.6	13.1	100			
	Separation Rate (EU)	−10.6	5.3	5.3	81.8	100		
	Job-finding Rate (UE)	−3.7	−2.3	−6.1	15.5	64.1	100	
	Wage volatility (SDTI)	−7.4	18.6	0.6	3.9	0.7	−5.3	100
		CPI	PRO	PRO2	U	EU	UE	SDTI
	Consumer price index (CPI)	100						
	Real productivity (PRO)	−3.7	100					
	Productivity secondary sector (PRO2)	−14.0	72.1	100				
Secondary	Unemployment rate (U)	−26.4	−0.4	7.3	100			
	Separation rate (EU)	−27.7	−8.3	2.4	77.3	100		
	Job-finding rate (UE)	14.9	−17.5	−12.9	−36.4	18.1	100	
	Wage volatility (SDTI)	−17.4	17.0	16.6	34.3	20.0	−32.7	100
		CPI	PRO	PRO3	U	EU	UE	SDTI
	Consumer price index (CPI)	100						
	Real productivity (PRO)	−3.7	100					
	Productivity tertiary sector (PRO3)	7.0	88.9	100				
Tertiary	Unemployment rate (U)	0.1	6.3	3.5	100			
	Separation rate (EU)	−2.2	−1.8	−1.3	68.6	100		
	Job-finding rate (UE)	13.9	−16.4	−9.1	−11.1	53.8	100	
	Wage volatility (SDTI)	−14.6	14.3	13.5	23.2	0.3	−29.0	100

Figure 2: Wage volatility, unemployment, separation, and job-finding rates in the primary sector (according to the national income quintile of the workers). Quarterly data 1996:1–2012:4

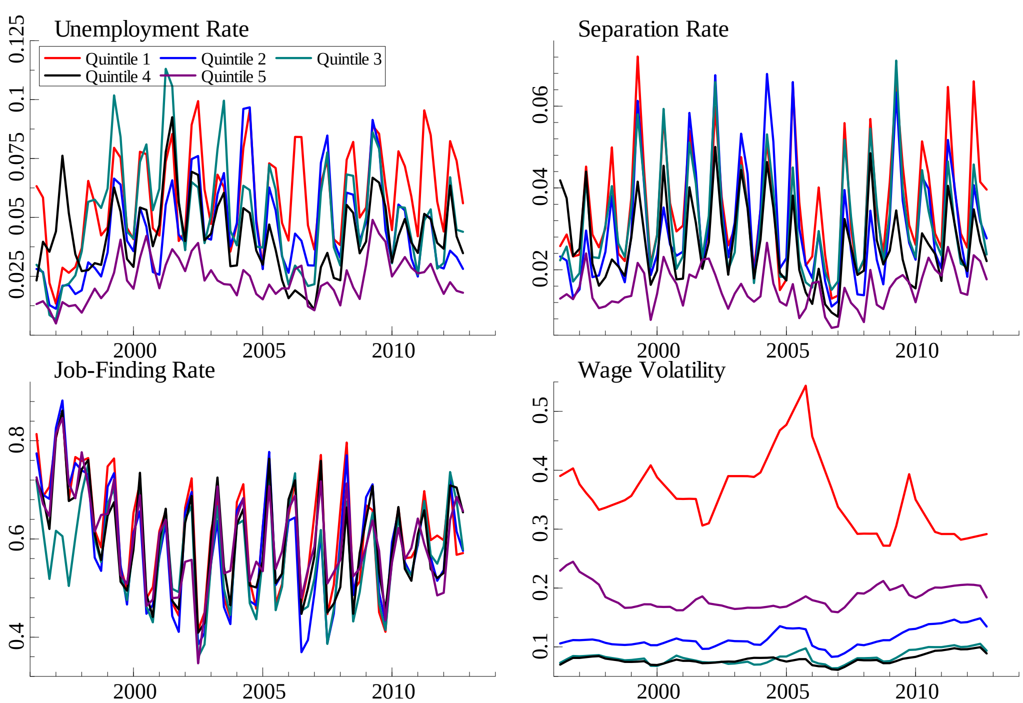


Figure 3: Wage volatility, unemployment, separation, and job-finding rates in the secondary sector (according to the national income quintile of the workers). Quarterly data 1996:1–2012:4

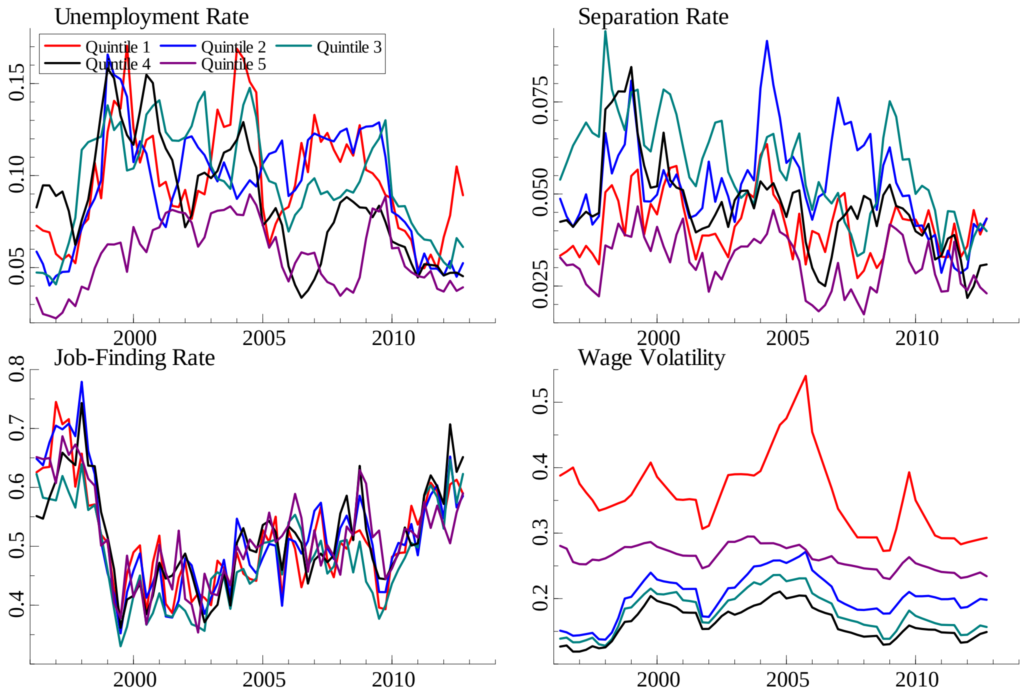
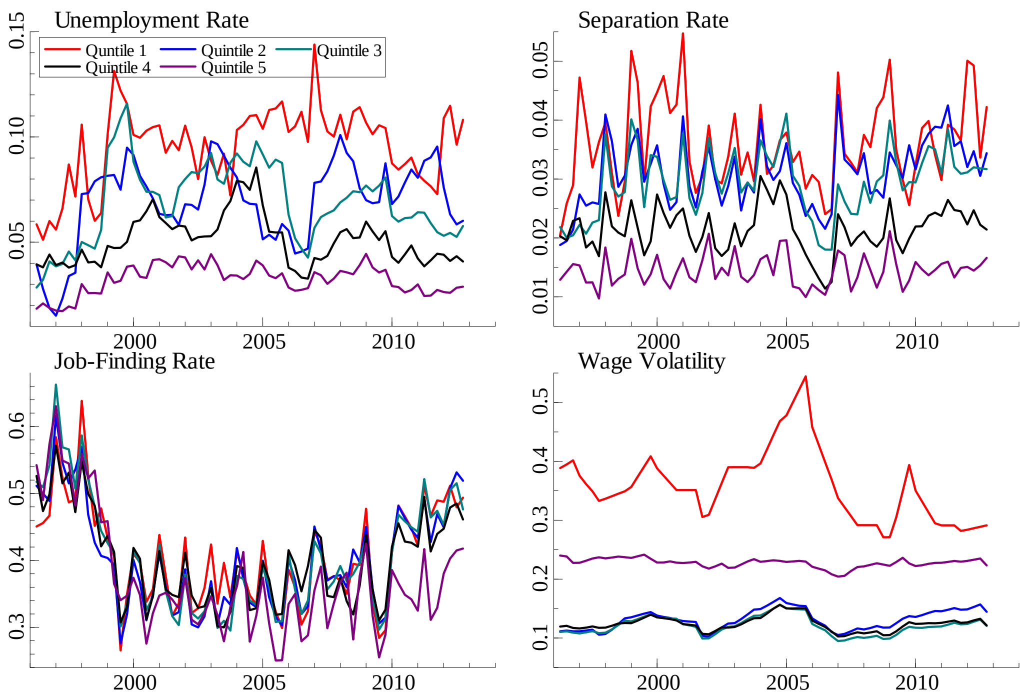


Figure 4: Wage volatility, unemployment, separation, and job-finding rates in the tertiary sector (according to the national income quintile of the workers). Quarterly data 1996:1–2012:4



3 The FAVAR model

We estimate a FAVAR model for the Chilean economy using macroeconomic data and the labor time series from Madeira (2015) for the quarterly period between 1996:2 and 2012:4. The FAVAR contains three lags and three unknown common factors,[2] and we assume that the only observable factor is the interest rate, as in Bernanke et al. (2005). The following system presents the model:

$$
\begin{aligned}
\begin{bmatrix} \boldsymbol{F} \\ \boldsymbol{Y} \end{bmatrix}_t &= \boldsymbol{\Phi}(L) \begin{bmatrix} \boldsymbol{F} \\ \boldsymbol{Y} \end{bmatrix}_{t-1} + \boldsymbol{\mu}_t \\
\begin{bmatrix} \boldsymbol{X} \\ \boldsymbol{Y} \end{bmatrix}_t &= \begin{bmatrix} \boldsymbol{\Lambda}^f & \boldsymbol{\Lambda}^y \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{F} \\ \boldsymbol{Y} \end{bmatrix}_t + \begin{bmatrix} \boldsymbol{e} \\ \boldsymbol{0} \end{bmatrix}_t
\end{aligned} \tag{1}
$$

where $\boldsymbol{F}$ is a 3-dimensional vector containing the unobservable factors, $\boldsymbol{Y}$ contains the interest rate, $\boldsymbol{\Phi}(L)$ is a lag operator of order 3, $\boldsymbol{\Lambda}^f$ is a matrix of parameters of dimension 142×3 indicating how each variable relates to the unobservable factors, and $\boldsymbol{\Lambda}^y$ is a matrix of parameters with dimension 142×1 that shows how the observable variables $\boldsymbol{X}$ relate to the interest rate. Finally, we assume that $\boldsymbol{\mu}_t \sim \mathcal{N}_4(\boldsymbol{0}, \boldsymbol{\Omega})$ and $\boldsymbol{e}_t \sim \mathcal{N}_{142}(\boldsymbol{0}, \boldsymbol{\Gamma})$, with $\boldsymbol{\mu}_t$ and $\boldsymbol{e}_t$ being independent.

[2]The results of the FAVAR estimation are robust to the use of an additional unknown factor.

$\boldsymbol{X}$ is a 142-dimensional vector containing 135 labor series and seven macroeconomics variables. The labor series includes the job-separation rate (EU, the employment to unemployment probability), the job-finding rate (UE, the unemployment to employment probability), and the standard deviation of the total labor earnings (SDTI) of the workers for each of 45 different demographic groups.[3] We classify each group according to age (16–35, 36–54, and 55 or older), economic sector[4] (primary, secondary, and tertiary sectors), and income quintile (with quintile 1 being the lowest income group and 5 the highest income). The seven macroeconomics variables include money stock (M3), consumer price index (CPI), real exchange rate (RER), copper price (CP), and productivity in the primary, secondary. and tertiary sector (PRO1, PRO2, and PRO3, respectively).[5] In addition, we classify all variables in $\boldsymbol{X}$ as slow-moving or fast-moving variables, where the former do not contemporaneously react to the interest rate. We extract the unobservable factors from the group of slow-moving variables in $\boldsymbol{X}$.

We estimate the system of equations using joint likelihood-based Gibbs sampling. That is, we calculate the characterization of the joint posterior density, $P\left(\boldsymbol{\theta}, \boldsymbol{F}^T \left| \boldsymbol{X}^T, \boldsymbol{Y}^T\right.\right)$, by sampling from the conditional densities $P\left(\boldsymbol{F}^T \left| \boldsymbol{\theta}, \boldsymbol{X}^T, \boldsymbol{Y}^T\right.\right)$ and $P\left(\boldsymbol{\theta} \left| \boldsymbol{F}^T, \boldsymbol{X}^T, \boldsymbol{Y}^T\right.\right)$, where a superscript T indicates that the respective vector[6] includes all the sample information from period 1 until period T and $\boldsymbol{\theta} = \left[\boldsymbol{\Lambda}^f, \boldsymbol{\Lambda}^y, \boldsymbol{\Gamma}, \operatorname{vec}(\boldsymbol{\Phi}), \boldsymbol{\Omega}\right]$. We estimated the model by imposing the restrictions $\boldsymbol{\Lambda}^f \boldsymbol{D}^{-1} = \boldsymbol{\Lambda}^f$ and $\boldsymbol{\Lambda}^y + \boldsymbol{\Lambda}^f \boldsymbol{D}^{-1} \boldsymbol{B} = \boldsymbol{\Lambda}^y$ to obtain a unique identification of the factors and their loadings, with $\boldsymbol{D}$ being a non-singular matrix and $\boldsymbol{B}$ a conformable matrix.

To account for the heterogeneity observed in the Chilean labor market, all variables in vector $\boldsymbol{X}$ must be simultaneously analyzed. Given the high dimension of $\boldsymbol{X}$, using a vector of autoregression (VAR) approach to analyze the transmission mechanism of a monetary shock would provide meaningless results because degrees of freedom are lost. VAR systems are normally estimated when the number of variables is relatively small (6–8 variables) and the size of the sample is large; the present case satisfies none of these conditions. Bernanke et al. (2005) suggested that a natural solution to the degrees-of-freedom problem is to use common factors to summarize large amount of information about the economy. Then augmenting a standard VAR by factors is a feasible strategy for analyzing large data set where the number of variables is much greater than the size of the sample. In addition, given the heterogeneity, the factors might capture some economic concept related to the labor variables.[7]

[3]We classify the 45 mutually exclusive groups according to the workers' ages, income quintiles and economic sectors. Let $i = 1, \ldots 45$ be expressed by a 3-dimensional vector z ={economic sector (m), age (n), income-quintile (q)}, with each variable assuming a set of discrete values: m ={1: Primary, 2: Secondary, 3: Tertiary}, n ={1: 16–35, 2: 36–54, 3: $\geq$55}, and q ={1, 2, 3, 4, 5}. Then $i = 1, .., 45$ corresponds to the following mutually exclusive values of matrix z: $1(z = [1, 1, 1])$, $2(z = [1, 1, 2]), \ldots,$ 45 $(z = [3, 3, 5])$.

[4]For further information see footnote 1.

[5]Appendix A describes the series, data sources, and transformations.

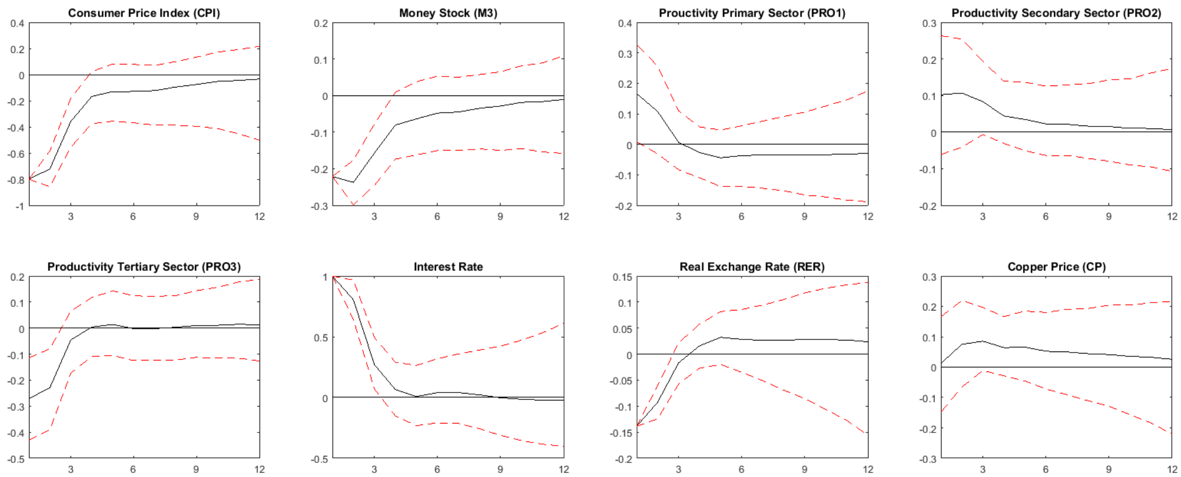
[6]For example, $\boldsymbol{Z}^T = [\boldsymbol{Z}_1, \boldsymbol{Z}_2, \ldots, \boldsymbol{Z}_T]$.

[7]The average R^2 of the system describing $\boldsymbol{X}$ in (1) is 65.6% and 53.2% for the job-finding rate (EU) and wage volatility (SDTI), respectively. This suggests that two of the three estimated factors are measuring some economic concept related to these labor variables.

4 Empirical results

We now present an impulse–response analysis of the transmission mechanism of a contractionary monetary shock. After estimating the FAVAR model, we analyze how a positive standard deviation shock to the interest rate affects the labor productivity (PRO) of each economic sector (primary, secondary, tertiary), the job-finding (UE) and job-separation (EU) rates, the wage volatility (SDTI), and the macroeconomic variables of money aggregate, CPI, and real exchange rate. Table 4 reports the summary of the responses, classified according to whether the variable experiences an increase, decrease, or no response after a contractionary monetary shock. Figure 5 shows the impulse response function for the macroeconomic variables in vector $\boldsymbol{X}$.

Figure 5: Impulse–response function of consumer price index, money stock M3, productivity in primary, secondary and tertiary sectors, real exchange rate, and copper price to one standard deviation positive shock to the interest rate



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

Note 3: By construction the impulse–response function of the interest rate starts at one (one standard deviation).

The upper part of Table 4 reports the response of the seven macroeconomic variables in vector $\boldsymbol{X}$. The value in brackets is the estimated duration time in quarters of the response to the contractionary monetary shock. In general, all the macroeconomic variables show correctly the expected sign response. For example the consumer price index (CPI), money stock (M3), and real exchange rate (RER) show a negative response lasting on average either three or four quarters to a contractionary monetary shock.[8] The copper price does not exhibit a significant response to an increase in the interest rate, which we expected because

[8]The economic response lasting three or four quarters is consistent with most of the VAR studies (Christiano et al., 1999). Furthermore, the fact that we do not find a price puzzle is worth emphasizing. Customarily, empirical data analysis finds a positive correlation between inflation and the interest rate, because policy makers typically increase interest rates to counteract periods of increasing inflation. Some studies use sign restrictions in the SVAR to identify shocks according to expected priors, which restrict the information to

Table 4: Response summary of macroeconomics variables and labor variables to one standard deviation positive shock to the interest rate

Variable	Increases	Decreases	No response
Macroeconomic variables			
Real money stock (M3)		(4)	
Consumer price index (CPI)		(4)	
Real exchange rate (RER)		(3)	
Real copper price (CP)			(0)
Real productivity primary sector (PRO1)	(1)		
Real productivity secondary sector (PRO2)			(0)
Real productivity tertiary sector (PRO3)		(3)	
Number of responses in labor variables			
Job-separation rate (EU)	20	2	23
Job-finding rate (UE)	10	10	25
Wage volatility (SDTI)	22	11	12

Note 1: The number in $(\cdot)$ is the length of the response, expressed in quarters.

Note 2: There are 45 mutually exclusive groups per labor variable (EU, UE, and SDTI). Each group is classified by economic sector, age, and income quintile. For further information, see Footnote 3.

the copper price is internationally determined. Productivity in the primary sector (PRO1) reacts positively to an increase in the interest rate, but this response lasts only one quarter, whereas the productivity in the tertiary sector shows a negative response that lasts three quarters. Finally, productivity in the secondary sector does not show a significant response.

Table 4 shows that in 20 of the 45 groups, job-separation rate (EU) reacts positively to a contractionary monetary shock and that only two groups exhibit a negative response. Therefore, an unemployment increase typically follows and interest rate increase. Furthermore, the results indicate that in 10 of the 45 groups the job-finding rate reacts negatively to an increase in the interest rate, whereas in the same number of groups the opposite reaction is observed. This seems to imply that recessions not only induce flows into unemployment but also create employment reallocation so that some sectors actually benefit from an increased number of workers looking for vacancies during a recession (Davis et al., 1998; Shimer, 2012; Elsby et al., 2013).

Given that labor intensity differs across economic sectors, how the labor variables respond to monetary shocks may depend on the economic sector analyzed. For example, the service sector is more labor intensive than the other sectors, suggesting that this sector might be more affected. To analyze this statement, Table 5 summarizes the responses of each labor market

get rid of price puzzle from the outset. We do not use this approach for three reasons. First, our sample is relatively short, and the identification of shocks using sign restrictions requires long time series for identification. Second, a VAR or SVAR works relatively well when the number of variables is not so big, but our study uses more than 100 labor market time series. Finally, when restrictions are imposed from the outset, it is difficult to discern which results are due to the assumptions made and which are due to the empirical facts (Christiano et al., 1999; Uhlig, 2005).

Table 5: Response of labor variables by economic sector to one standard deviation positive shock to the interest rate

Sector	Variable	Number of each type of response		
		Increase	Decrease	No response
Primary	Job-separation rate (EU)	6	1	8
	Job-finding rate (UE)	3	1	11
	Wage volatility (SDTI)	3	8	4
Secondary	Job-separation rate (EU)	10	0	5
	Job-finding rate (UE)	1	5	9
	Wage volatility (SDTI)	10	0	5
Tertiary	Job-separation rate (EU)	4	1	10
	Job-finding rate (UE)	6	4	5
	Wage volatility (SDTI)	9	3	3

Note 1: In each sector there are 45 mutually exclusive groups (15 per labor variable) classified by age and income quintile. For further details, see Footnote 3.

variable (job-separation rate, job-finding rate, and wage volatility) by economic sector.[9]

Table 5 shows that the secondary sector is the most affected in the economy when we look at the response of the job-separation rate (EU). In 10 out of 45 groups in the secondary sector, an increase in the separation rate occurs after a contractionary monetary shock, compared to six and four groups in the primary and service sector, respectively. Table 4 showed that job-finding rate reacts negatively to an interest rate increase for 10 of the 45 different demographic groups, and Table 5 finds that the probability that a worker will be hired after a contractionary monetary shock is lower both in the secondary and tertiary sectors (where five and four demographic groups are affected, respectively).

Finally, Table 4 showed that the standard deviation of earnings increases in 22 out of the 45 groups. Most of these groups belong to the secondary sector in the economy, as Table 5 shows. This result matches empirical evidence found for the United States, which shows that idiosyncratic income risk increases during recessions (Storesletten et al., 2001, 2004; McKay and Papp, 2011; Davis and von Wachter, 2011; Guvenen et al., 2014).

The following analysis classifies the response of the labor flow variables and wage volatility (EU, UE, and SDTI) by demographic group and economic sector. Each demographic group is represented by the pair (n, q), where n is an age classification, $n = \{1\text{: } (16–35),\ 2\text{: } (36–54),\ 3\text{: } (\geq 55)\}$, and q is the worker's income quintile, $q = \{1, 2, 3, 4, 5\}$. For example, (3,5) is the group of workers aged 55 or older whose income belongs to the fifth quintile. Therefore, for each labor flow variable there are 45 mutually exclusive groups.

Table 6 shows the employment in each demographic group, presenting the information relative to the employment in both the whole economy and each economic sector. The tertiary sector, with a rate of 63.2%, concentrates most of the employment in the economy, followed by the secondary sector (22.2%) and the primary sector (14.6%). Within each sector, the

[9] In Appendix B we show the impulse–response function of the job-separation rate, job-finding rate, and wage volatility for all combinations of age, income quintile, and economic sector.

group of mid-age workers (36–54) has the most employed people (45.8%, 48.9%, and 48.6% in the primary, secondary, and tertiary sector, respectively). Moreover, the group of older workers (55 or older) with income in the first quintile has the lowest rate in each sector (2.2%, 1.3%, and 1.6% in the primary, secondary, and tertiary sector, respectively).

Table 6: Participation of employment (%) of demographics groups in total employment and employment by sector (average 1996:2–2012:4)

Group (age,quintile)	Sector			Total [5,934,921.9]
	Primary [864,089.5] 14.6%	Secondary [1,319,939.5] 22.2%	Tertiary [3,750,892.9] 63,2%	
(1,1)	8.2	3.7	5.6	5.6
(1,2)	10.9	10.0	8.3	9.0
(1,3)	7.9	10.8	8.5	8.9
(1,4)	3.9	8.4	7.6	7.3
(1,5)	2.7	5.0	6.2	5.4
Subtotal	33.6	37.9	36.2	36.2
(2,1)	5.8	3.9	5.5	5.2
(2,2)	10.4	7.3	7.2	7.7
(2,3)	12.7	11.1	8.8	9.9
(2,4)	8.8	14.2	11.7	11.8
(2,5)	8.1	12.4	15.4	13.6
Subtotal	45.8	48.9	48.6	48.2
(3,1)	2.2	1.3	1.6	1.6
(3,2)	4.3	1.8	1.8	2.2
(3,3)	5.2	2.5	2.3	2.8
(3,4)	4.8	4.0	3.7	3.9
(3,5)	4.1	3.8	5.7	5.0
Subtotal	20.6	13.4	15.1	15.5
Total	100	100	100	100

Note 1: [·] is the average number of employed people.

Note 2: (n, q) is a (age, quintile) group. $n = \{1\text{: } (16\text{–}35),\ 2\text{: } (36\text{–}54),\ 3\text{: } (\geq 55)\}$, and q is the worker's income quintile, $q = \{1, 2, 3, 4, 5\}$.

Tables 7, 8, and 9 report the qualitative responses for each economic sector about whether a variable increases, decreases or shows no response after a contractionary monetary shock. Basically, these tables expand Table 5 by showing exactly the age group and income quintile of the workers affected by monetary shocks within each economic sector. In addition, these tables provide a basic summary of the qualitative responses of the individual impulse–response graphs shown in Appendix B.

Some results stand out. Within the primary sector, Table 7 suggests that after a contractionary monetary shock, the separation rate increases for the oldest workers (55 or older) in the income quintiles 3 and 5 and for the mid-age workers (36–54) in income quintiles 1, 2 and 3. Therefore, the separation rate change is most clear-cut for the oldest workers with income equal to or above that of the middle class and for the mid-age workers with income equal to or below that of the middle class. Then, a contractionary monetary shock is likely to affect negatively the employment of 49.1% of people working in the primary sector (see Table 6) Furthermore, after a contractionary monetary shock, the primary sector workers in the age interval 16–35 and in the lowest-income quintile are less likely to find a job. In the primary sector wage volatility also increases for the workers in the lowest-income quintile; this applies for all age groups. However, in the primary sector wage volatility actually declines for older workers (55 or older) and mid-age workers (36–54) across all income ranges.

Within the secondary sector, Table 8 shows that almost all groups of workers suffer an increase in the job-separation rate after a contractionary monetary shock. Moreover, mid-age workers (36–54) in the mid-income range (quintiles 2 and 3) and the youngest workers (16–35) suffer a decrease in their job-finding rate. Therefore, the secondary sector suffers a double impact of a contractionary monetary shock that increases job destruction (73.4% of people working in the secondary sector are likely to move into unemployment) and decreases job creation (40.5% of people working in the secondary sector are likely to experience a decrease in the probability of finding a job). Also, almost all groups of workers in the secondary sector experience an increase in their wage volatility after a contractionary shock.

Table 9 shows that in the tertiary sector only the oldest workers (55 and older) suffer an increase in their separation rate after a contractionary monetary shock (this represents 11.4% of the people working in the tertiary sector), whereas the youngest workers (16–35) are the only ones that experience a decrease in their job-finding rate; this group represents 30% of the people working in the tertiary sector. These groups also see an increase in wage volatility after a contractionary shock. Therefore, the results for the secondary and tertiary sectors show that idiosyncratic wage risk is counter-cyclical in Chile just as for the United States (Storesletten et al., 2001, 2004; McKay and Papp, 2011).

Thus, after a contractionary monetary shock, the FAVAR analysis shows that job-separation rate will increase relatively more in the secondary sector, job-finding rate will drop, and people between the ages of 16 and 35 are the most affected in the secondary and tertiary sectors. These results suggest that in periods where contractionary monetary policy is at work, other economic policies (e.g., fiscal policy) should stimulate employment in the secondary sector and, particularly, employment of the youth in both the tertiary and secondary sector. Given that the youth group normally consists of unskilled and inexperienced people and that an increase in the interest rate is likely to decrease the probability of finding a job for this group, an economic policy that increases the human capital of the youth (e.g., job training, higher education) and stimulates the hiring of people between 16 and 35 is likely to counteract the negative effects of a contractionary monetary shock.

Table 7: Response of labor variables in the primary sector by age and income quintile to o one standard deviation positive shock to the interest rate

	Job-separation rate (EU) response
Increase	(1,2), (2,1), (2,2), (2,3), (3,3), (3,5)
Decrease	(3,4)
No response	(1,1), (1,3), (1,4), (1,5), (2,4), (2,5), (3,1), (3,2)
	Job-finding rate (UE) response
Increase	(1,4), (2,3), (2,4)
Decrease	(1,1)
No response	(1,2), (1,3), (1,5), (2,1), (2,2), (2,5), (3,1), (3,2), (3,3), (3,4), (3,5)
	Wage volatility (SDTI) response
Increase	(1,1), (2,1), (3,1)
Decrease	(1,2), (2,2), (2,4), (2,5), (3,2), (3,3), (3,4), (3,5)
No response	(1,3), (1,4), (1,5), (2,3)

Note 1: (n, q) is a (age, quintile) group. $n = \{1\text{: } (16\text{–}35),\ 2\text{: } (36\text{–}54),\ 3\text{: } (\geq 55\ )\}$, and q is the worker's income quintile, $q = \{1,\ 2,\ 3,\ 4,\ 5\}\}$.

Table 8: Response of labor variables in the secondary sector by age and income quintile

	Job-separation rate (EU) response
Increase	(1,3), (1,4), (1,5), (2,1), (2,3), (2,4), (2,5), (3,1), (3,3), (3,5)
Decrease	-
No response	(1,1), (1,2), (2,2), (3,2), (3,4)
	Job-finding rate (UE) response
Increase	(3,2)
Decrease	(1,1), (1,2), (1,4), (2,2), (2,3)
No response	(1,3), (1,5), (2,1), (2,4), (2,5), (3,1), (3,3), (3,4), (3,5)
	Wage volatility (SDTI) response
Increase	(1,1), (1,2), (1,3), (1,4), (1,5), (2,1), (2,2), (2,3), (2,4), (3,1)
Decrease	-
No response	(2,5), (3,2), (3,3), (3,4), (3,5)

Note 1: (n, q) is a (age, quintile) group. $n = \{1\text{: } (16\text{–}35),\ 2\text{: } (36\text{–}54),\ 3\text{: } (\geq 55)\}$, and q is the worker's income quintile, $q = \{1,\ 2,\ 3,\ 4,\ 5\}$.

Table 9: Response of labor variables in the service sector by age and income quintile

	Job-separation rate (EU) response
Increase	(3,1), (3,2), (3,3), (3,5)
Decrease	(1,4)
No response	(1,1), (1,2), (1,3), (1,5), (2,1), (2,2), (2,3), (2,4), (2,5), (3,4)
	Job-finding rate (UE) response
Increase	(2,4), (3,1), (3,2), (3,3), (3,4), (3,5)
Decrease	(1,1), (1,2), (1,3), (1,4)
No response	(1,5), (2,1), (2,2), (2,3), (2,5)
	Wage volatility (SDTI) response
Increase	(1,1), (1,2), (1,3), (1,4), (2,1), (3,1), (3,2), (3,3), (3,4)
Decrease	(2,2), (2,3), (2,5)
No response	(1,5), (2,4), (3,5)

Note 1: (n, q) is a (age, quintile) group. $n = \{1\text{: } (16–35),\ 2\text{: } (36–54),\ 3\text{: } (\geq 55)\}$, and q is the worker's income quintile, $q = \{1, 2, 3, 4, 5\}$.

5 Conclusion

We analyze how monetary policy affects labor markets with a special focus on the heterogeneity of different economic sectors and demographic groups. We find that there is indeed heterogeneity of how different economic sectors react to monetary shocks. While fluctuations in real labor productivity growth are strongly correlated across different sectors, clear differences are evident in terms of the behavior of employment flows. Labor productivity growth in each economic sector has a low correlation with business cycle fluctuations in the unemployment rate and flows into and out of unemployment. We also show that fluctuations in unemployment rates have a high correlation with changes in job-separation rates. This seems to support the empirical evidence found for other countries that job destruction plays a crucial role in explaining cyclical unemployment fluctuations (Elsby et al., 2013).

After a contractionary monetary shock, the secondary sector reacts most strongly in terms of both an increased job-separation rate and a decreased job-finding rate. Also, real labor productivity falls in the tertiary sector after an interest rate shock, in contrast to the primary and secondary sectors. For the primary and tertiary sectors, it is mostly the older workers (55 or older) who experience an increase in the job-separation rate, while in the secondary sector the impact on job destruction is felt across all ages and income levels.

Finally, we find that the idiosyncratic volatility of labor earnings increases in both the secondary and tertiary sectors after a contractionary monetary shock, confirming similar results found for the United States (Storesletten et al., 2004; McKay and Papp, 2011). This increase in idiosyncratic earnings risk is also found for the lowest-income workers in the primary sector.

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A Data

In Appendix A and B, the index $i = 1, .., 45$ corresponds to 45 mutually exclusive groups classified according to the workers' ages, income quintiles, and economic sectors. Let i be expressed by a 3-dimensional vector $z =${economic sector (m), age (n), income-quintile (q)}, with each variable assuming respectively a set of discrete values: $m =${1: Primary, 2: Secondary, 3: Tertiary}, $n =${1: 16–35, 2: 36–54, 3: $\geq$55}, and $q =${1, 2, 3, 4, 5}. Then $i = 1, .., 45$ corresponds to the following mutually exclusive values of matrix $z : 1(z = [1, 1, 1])$, $2(z = [1, 1, 2]), \ldots,$ 45 $(z = [3, 3, 5])$.

Table A.1: Data source, description and transformation

Variable	Description	Source	Transformation	Slow code
M3	Real money stock M3	Central Bank of Chile	log difference	0
CPI	Consumer Price Index	Central Bank of Chile	difference of growth rate	1
I1	1-year real interest rate	Central Bank of Chile	-	0
PRO1	Real productivity primary sector	Our own calculation	log difference	1
PRO2	Real productivity secondary sector	Our own calculation	log difference	1
PRO3	Real productivity service sector	Our own calculation	log difference	1
CP	Real copper price	Central Bank of Chile	log difference	1
RER	Real exchange rate	Central Bank of Chile	log difference	0
EUi	Job-separation rate	Madeira (2015)	-	1
UEi	Job-finding rate	Madeira (2015)	-	1
SDTIi	Mean Standard Deviation of the idiosyncratic annual change in total labor income	Madeira (2015)	difference	1

Note 1: All variables are seasonally adjusted using the Census X13 program.

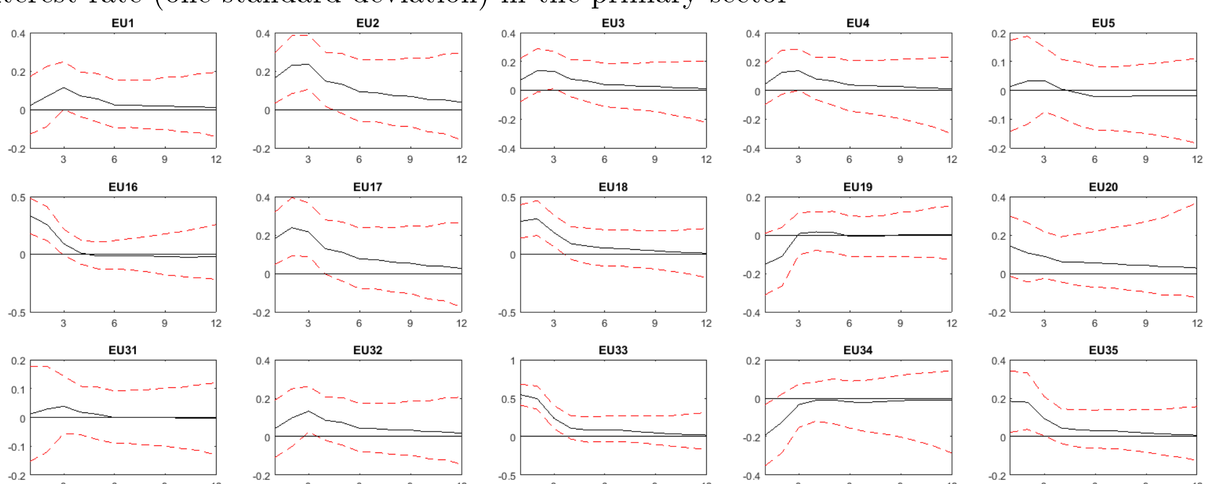
Note 2: Slow code: 1 stands for a slow-moving variable and 0 for a fast-moving variable. A slow moving variable does not contemporaneously react to the interest rate.

Note 3: The 1-year interest rate is the nominal average weighted interest rate of the financial system for operations of 90 days to 1 year, deflated by the inflation rate based on the log difference of the CPI.

Note 4: Real Productivity is obtained by the ratio of the total aggregate value-added of each economic sector (published by the Central Bank of Chile) divided by the number of workers in each sector as given by the quarterly National Employment Survey (ENE) calculated by Madeira (2015).

B Impulse–response functions

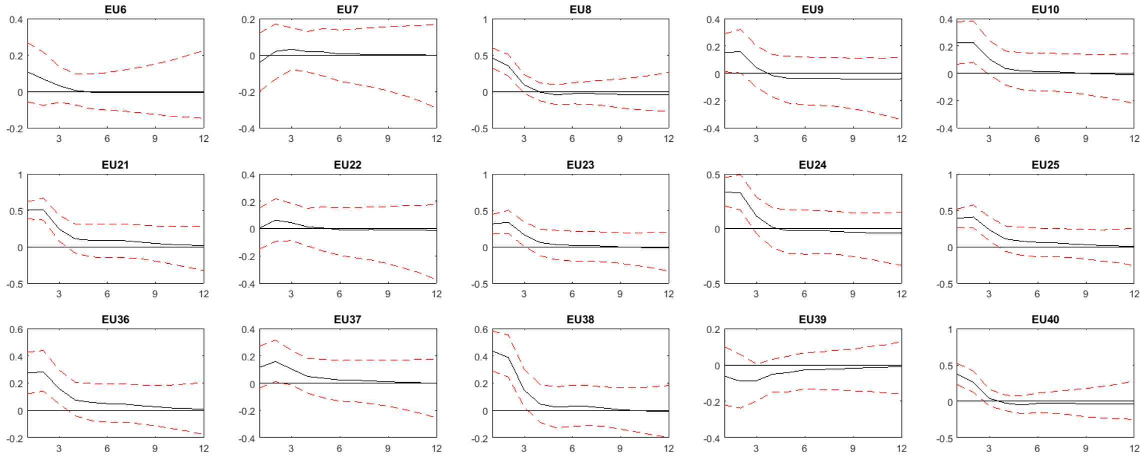
Figure A.1: Impulse–response of the job-separation rate (EUi) to a positive shock to the interest rate (one standard deviation) in the primary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

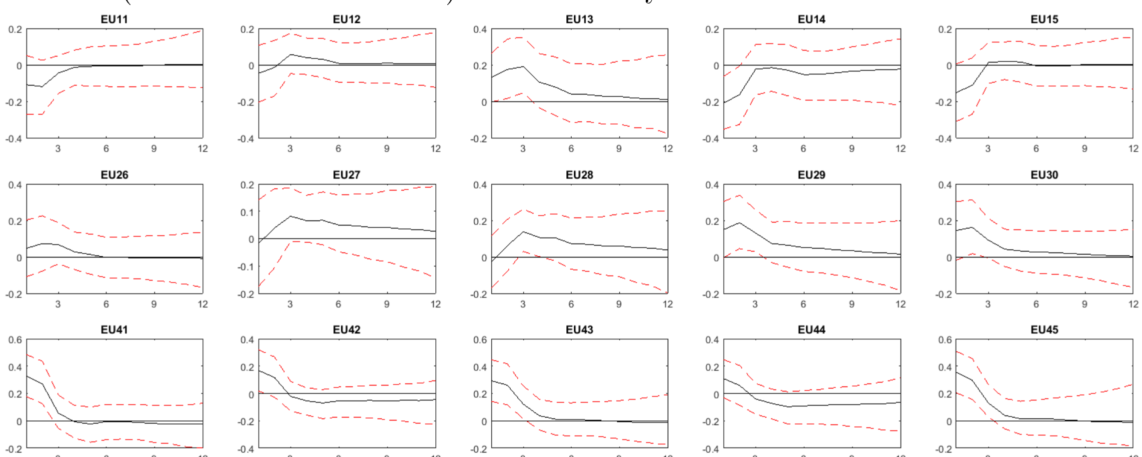
Figure A.2: Impulse–response of the job-separation rate (EUi) to a positive shock to the interest rate (one standard deviation) in the secondary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

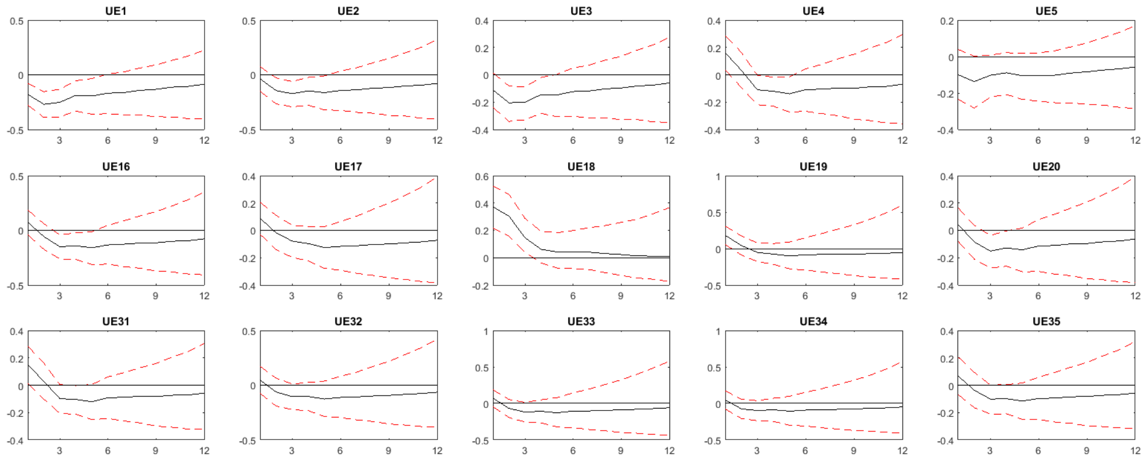
Figure A.3: Impulse–response of the job-separation rate (EUi) to a positive shock to the interest rate (one standard deviation) in the tertiary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

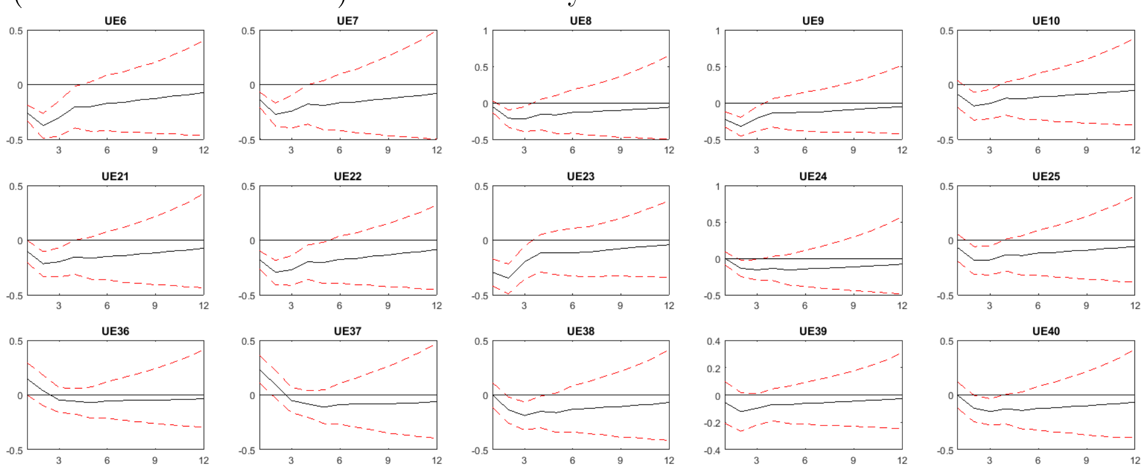
Figure A.4: Impulse–response of job-finding rate (UEi) to a positive shock to the interest rate (one standard deviation) in the primary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

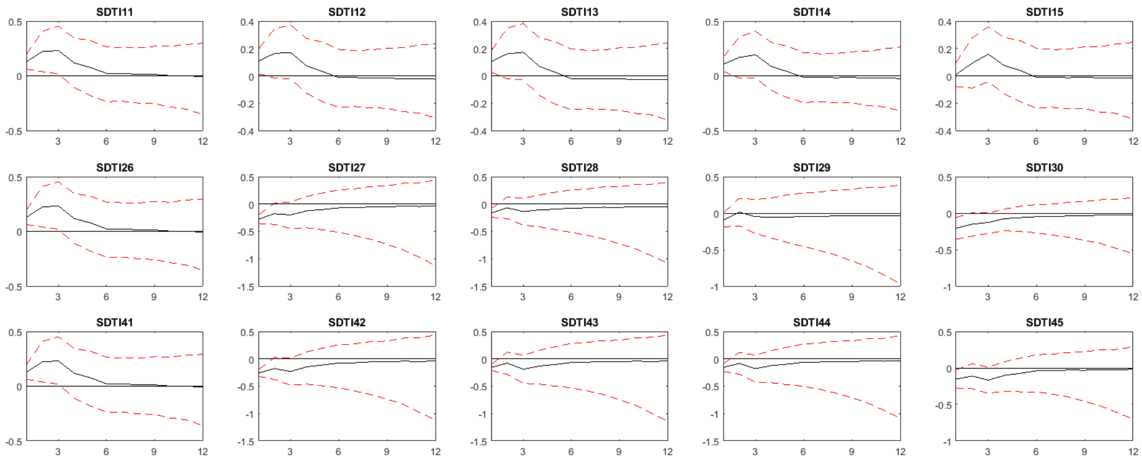
Figure A.5: Impulse–response of job-finding rate (UEi) to a positive shock to the interest rate (one standard deviation) in the secondary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

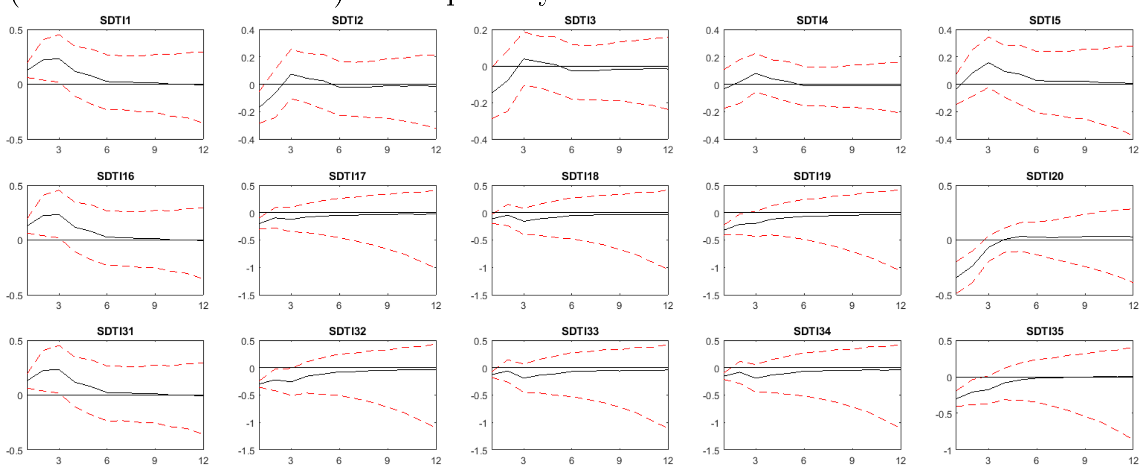
Figure A.6: Impulse–response of job-finding rate (UEi) to a positive shock to the interest rate (one standard deviation) in the tertiary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

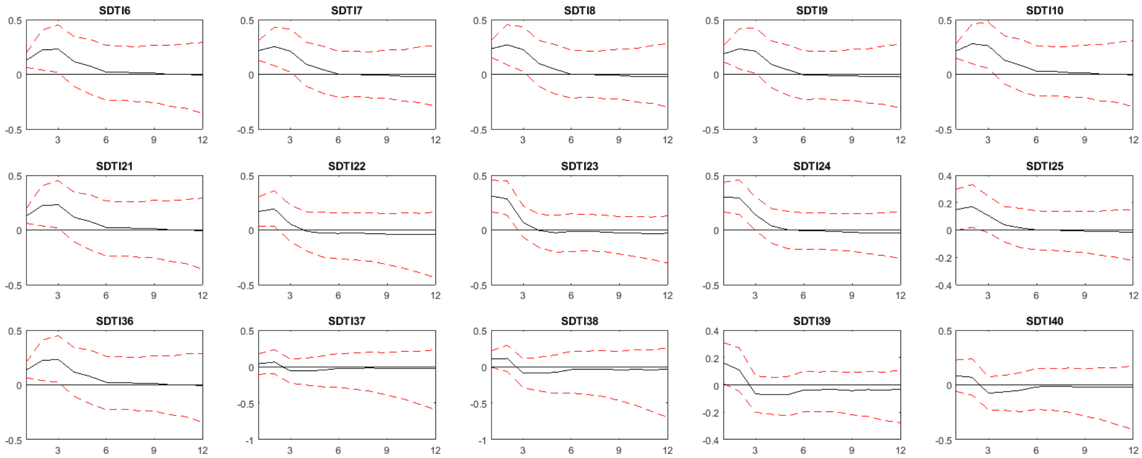
Figure A.7: Impulse–response of the wage volatility (SDTIi) to a positive shock to the interest rate (one standard deviation) in the primary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

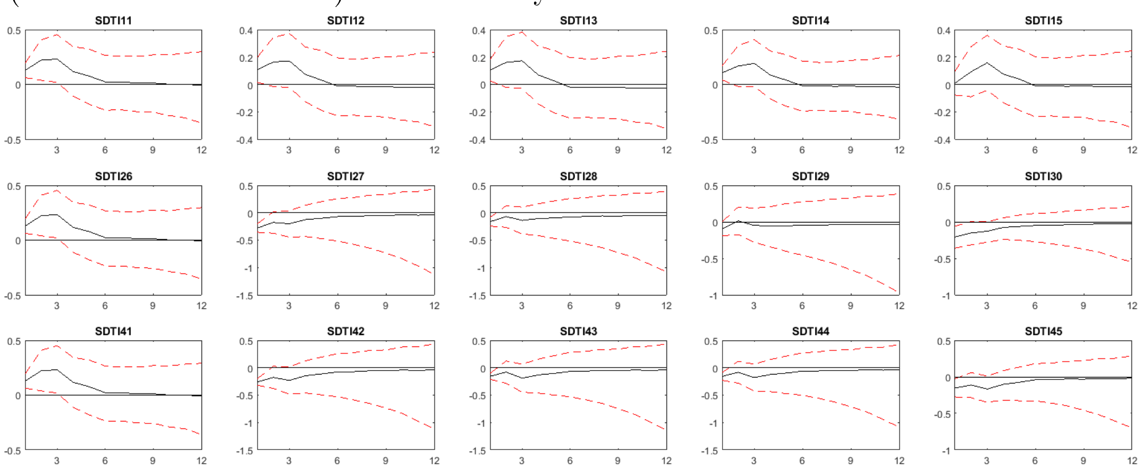
Figure A.8: Impulse–response of the wage volatility (SDTIi) to a positive shock to the interest rate (one standard deviation) in the secondary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.

Figure A.9: Impulse–response of the wage volatility (SDTIi) to a positive shock to the interest rate (one standard deviation) in the tertiary sector



Note 1: The black graph is the response, in standard deviation units, to one standard deviation positive shock to the interest rate.

Note 2: The dotted red graphs are the 90% confidence interval of the impulse–response function.