Labor Supply Factors and Economic Fluctuations*

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Abstract

We propose a new VAR identification scheme that enables us to identify labor supply shocks from other labor market shocks. Identification is achieved by imposing robust sign-restrictions that are derived from a theoretical model. According to our analysis on US data over the period 1985-2014, labor supply shocks and wage bargaining shocks are important drivers of output and unemployment both in the short-run and in the long-run. These results suggest that identification strategies used in estimated New Keynesian models to disentangle labor market shocks may be misguided. We also analyze the behavior of the labor force participation rate through the lenses of our model. We find that labor supply shocks are the main drivers of the participation rate and account for about half of its decline in the aftermath of the Great Recession.

Keywords: labor supply shocks, wage mark-up shocks, identification, VAR, labor force participation

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1 Introduction

What is the importance of disturbances originating in the labor market in driving economic fluctuations? A vast literature has shown that procyclical movements in the difference between the marginal rate of substitution and the marginal product of labor (for example Hall 1997, and Chari, Kehoe and McGrattan 2007) can account for a sizeable share of fluctuations in hours worked and output at business-cyle frequencies. This "labor wedge" has often been interpreted as arising from labor market shocks, either exogenous shifts in the disutility of supplying labor or movements in wage-markups. The objective of this paper is to quantify the importance of these different labor market shocks for economic fluctuations in the context of a Vector Auto Regressive (VAR) model.

We propose a new VAR identification scheme based on sign-restrictions [1] that enables us to disentangle labor supply shocks from another identified labor market shock that we call a "wage bargaining shock". The sign-restrictions are derived from a New Keynesian model with search and matching frictions in the labor market and endogenous labor force participation and are shown to be robust to parameter uncertainty. Our key contribution is to use data on unemployment and labor force participation to disentangle the two shocks. In the theoretical model, unemployment and participation are procyclical in response to labor supply shocks and countercyclical in response to wage bargaining shocks. This asymmetric behavior of unemployment and participation in response to the two shocks is used as a sign-restriction in the VAR. Our second and related contribution is to show that labor supply shocks and wage bargaining shocks[2] can be separately identified within the context of our theoretical framework. These two shocks have been shown to be observationally equivalent in the standard New Keynesian model. The presence of search frictions in the labor market and of the labor force participation margin in our model helps solve this issue.

The main result that emerges from our VAR analysis is that *both* shocks originating in the labor market are important drivers of output and unemployment fluctuations. Labor supply shocks are particularly relevant to capture macroeconomic dynamics at low frequencies since they account for more than 60% of fluctuations in output and 50% in unemployment in the long-run. Wage bargaining shocks are more important at short horizons but also play a non-negligible role in the long-run, especially for unemployment. These results are related to a previous literature that investigates the role of labor supply shocks in VAR models. Shapiro and Watson (1988) consider demand, technology and labor supply shocks. They assume that the long-run level of output is only determined by technology shocks and labor supply shocks, thus extending the Blanchard and Quah (1988) methodology. Moreover, they assume that the the long-run labor supply is not influenced by aggregate demand and the level of technology.

[1] The use of sign restrictions in VAR model has been pioneered by Faust (1998), Uhlig (2005) and Canova and De Nicolo' (2002). We follow Canova and Paustian (2011), Pappa (2009) and Peersman and Straub (2009) among others in deriving sign restrictions from a theoretical model. Earlier papers using sign restricted VAR models to investigate labor market dynamics are Fujita (2011) and Benati and Lubik (2014).

[2] Shocks to the wage equation assume different names in alternative set-ups. In New Keynesian models with monopolistically competitive labor markets they are named wage mark-up shocks whereas in models with search and matching frictions in the labor market they are named wage bargaining shocks. Notice, however, that wage mark-up shocks are often interpreted as variations in the bargaining power of workers (cf. Chari, Kehoe and McGrattan, 2009). For consistency with the previous literature, we will name the wage shocks as wage mark-up or wage bargaining shocks according to the structure of the labor market.

They find that labor supply shocks are the most important driver of output and hours in the long-run. More surprisingly, they also find that labor supply shocks are extremely important in the short run. While this result goes against the "conventional wisdom" that labor supply shocks should matter only in the long run, subsequent papers have confirmed the relevance of labor supply shocks at business cycle frequencies (cf. Chang and Schorfheide, 2003, on US data and Peersman and Straub, 2009, on Euro area data) in VAR models identified with sign restrictions. We contribute to this literature by refining the identification of labor supply shocks: the previous VAR studies did not disentangle labor supply shocks from wage mark-up shocks. Nevertheless, our results are broadly consistent with the previous literature in finding an important role for labor supply shocks at all horizons.

Our results are also related to previous studies in the Dynamic Stochastic General Equilibrium (DSGE) literature dealing with shocks originating in the labor market. As previously mentioned, a large literature has identified the gap between households' marginal rate of substitution and the marginal product of labor as an important driving force of business cycle fluctuations. Smets and Wouters (2003) and Chari, Kehoe and McGrattan (2009) observed that in a New Keynesian model this wedge could either be interpreted as an efficient shock to preferences or as an inefficient wage-markup shock. Justiniano, Primiceri and Tambalotti (2013) and Smets and Wouters (2003) distinguish these two interpretations on the basis of the persistence in the exogenous processes: wage mark-up shocks are assumed to be independent and identically distributed whereas labor supply shocks are modeled as persistent processes. This identification strategy may solve the observational equivalence in the very short run but rules out any role for wage mark-up shocks at longer horizons. Gali', Smets and Wouters (2011) propose a reinterpretation of the standard New Keynesian model in which unemployment emerges because of the monopoly power of unions. In that set-up wage mark-up shocks and labor supply shocks are no longer observationally equivalent. However long-run movements in unemployment are assumed to be exclusively driven by wage-markup shocks. Therefore, our reading of the previous literature is that only polar assumptions have been used to disentangle the two labor market shocks. According to our results, these polar assumptions do not find support in the data: *both* our identified wage bargaining shocks and labor supply shocks play a role in the short run *and* in the long-run.

In addition, we analyze the behavior of the labor force participation rate in the US through the lenses of our VAR model. We find that labor supply shocks are the main drivers of the participation rate and account for about half of its decline in the aftermath of the Great Recession. The remaining share of the decline is mainly explained by negative demand shocks and wage bargaining shocks. Analysis of the recent decline in the participation rate in the US include Bullard (2014), Daly and Valletta (2014), Erceg and Levin (2013), Fujita (2014), Hornstein (2013) and Kudlyak (2014) among others. To the best of our knowledge, we are the first to provide a VAR perspective on this issue. Our work is also related to recent papers studying the dynamics of the participation rate. Barnichon and Figura (2011 and 2014) use micro data on labor market flows to analyze the role of demographic and other labor supply factors in explaining Beveridge curve dynamics and the downward trends in participation and in unemployment. Elsby, Hobjin and Sahin (2015) show how a flows-based decomposition of the variation in labor market stocks reveals that transitions at the participation margin account for around one-third of the cyclical variation in the unemployment rate. Arseneau and Chugh (2012), Campolmi and Gnocchi (2014) and Christiano, Eichenbaum and Trabandt (2014) among others model the participation decision in the context of DSGE models. Christiano, Trabandt and Walentin (2012) and Gali' (2011) study the response of the participation rate to monetary, technology and investment-specific shocks in VAR models identified with long-run restrictions. We also provide evidence on the response of participation to different shocks using an alternative identification scheme.

The paper is structured as follows. Section 2 develops a New Keynesian model with labor market frictions and endogenous labor force participation. In Section 3 this model is used to derive robust sign restrictions that we use to identify structural shocks in a VAR model estimated with Bayesian methods. Section 4 presents the results. Section 5 discusses the participation rate dynamics whereas Section 6 further refines the interpretation of the wage bargaining shock and disentangles it into different components. Finally, Section 7 concludes.

2 Model

This section develops a model which departs from the standard New Keynesian model in several ways. First, the labor market is not perfectly competitive but is characterized by search and matching frictions. Second, the labor force participation decision is modelled explicitly. The economy consists of two sectors of production. Wholesale firms operate in perfectly competitive markets. They use labor as the sole input in the production process and have to post vacancies in order to match with workers. Their output is sold to monopolistically competitive retail firms which transform the homogeneous goods one for one into differentiated goods and face staggered price adjustment. Individual workers can be in three different labor-market states: employment, unemployment, and outside the labor force (which we also refer to as non-participation).

2.1 Labor market

The size of the population is normalized to unity. Workers and firms need to match in the labor market in order to become productive. The number of matches in period t is given by a Cobb-Douglas matching function $m_t = \Gamma_t s_t^{\alpha} v_t^{1-\alpha}$, s_t being the number of job-seekers and v_t the number of vacancies posted by firms. The parameter Γ_t reflects the efficiency of the matching process. It follow the autoregressive process $ln(\Gamma_t) = (1-\zeta^{\Gamma})ln(\Gamma) + \zeta^{\Gamma} ln(\Gamma_{t-1}) + \epsilon_t^{\Gamma}.\alpha \in [0,1]$ is the elasticity of the matching function with respect to the number of job seekers. Define $\theta_t = \frac{v_t}{s_t}$ as labor market tightness. The probability q_t for a firm to fill a vacancy and the probability p_t for a worker to find a job are respectively $q_t = \frac{m_t}{v_t} = \Gamma_t \theta_t^{-\alpha}$ and $p_t = \frac{m_t}{s_t} = \Gamma_t \theta_t^{1-\alpha}$.

At the end of each period, a fraction ρ of existing employment relationships is exogenously destroyed. We follow Christiano, Eichenbaum and Trabandt (2014) and assume that both those ρN separated workers and the $L-N$ unemployed workers face an exogenous probability of exiting the labor force $1-\omega$, ω being the "staying rate"[3]. At the beginning of the following period, the representative household chooses the number of non-participants r it transfers to the labor

[3] As in Christiano, Eichenbaum and Trabandt (2014), we introduce this staying rate to account for the fact that workers move in both direction between unemployment, employment and participation. However, the introduction of ω has no impact on the equilibrium conditions of the model. The household adjusts r_t according to the value of ω in order to reach its desired value of L_t. We check that $r_t > -\omega(L_t - (1-\rho)N_{t-1})$ holds in every periods, that is, that the number of job seekers is always positive.

force. The size of the labor force in period t is thus given by $L_t = \omega(L_{t-1} - N_{t-1} - \rho N_{t-1}) + (1 - \rho)N_{t-1} + r_t$ and the number of job seekers by $s_t = \omega(L_{t-1} - (1-\rho)N_{t-1}) + r_t = L_t - (1-\rho)N_{t-1}$. Employment evolves according to the following law of motion

$$N_t = (1-\rho)N_{t-1} + \Gamma_t s_t^{\alpha} v_t^{1-\alpha} \tag{1}$$

New hires become productive in the period and separated workers can find a job immediately with a probability given by the job finding rate, in keeping with the timing proposed by Ravenna and Walsh (2008). The unemployment rate in period t is $u_t = \frac{L_t - N_t}{L_t}$.

2.2 Households

The representative household consists of a continuum of measure one of infinitely lived members indexed by $i \in [0,1]$ who pool their consumption risk, following Merz (1995). i determines the disutility of participating of each individual. The latter is given by $\chi_t i^{\varphi}$ if the individual participates in the labor force and zero otherwise. χ_t is an exogenous preference shifter which evolves according to the stochastic process $ln(\chi_t) = (1-\zeta^{\chi})ln(\chi) + \zeta^{\chi} ln(\chi_{t-1}) + \epsilon_t^{\chi}$. φ is a parameter determining the shape of the distribution of work disutilities across individuals. The utility of each family member is given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_{it}^{1-\sigma}}{1-\sigma} - \chi_t 1_{it} i^{\varphi} \right]$$

where 1_{it} is an indicator function taking a value of 1 if individual i is employed in period t and 0 otherwise, β the rate of time preference, σ the coefficient of risk aversion and C_{it} individual's i consumption of the final good. Full sharing of consumption among household members implies $C_{it} = C_t$ for all i. The household's aggregate utility function is then given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \chi_t \frac{L_t^{1+\varphi}}{1+\varphi} \right] \tag{2}$$

The household chooses C_t, B_{t+1}, N_t and L_t so as to maximize (2) subject to its budget constraint and its perceived law of motion of employment

$$P_t C_t + (1+I_t)^{-1} \frac{B_{t+1}}{\varepsilon_t^p} = P_t \left[w_t N_t + b_t (L_t - N_t) \right] + B_t + P_t \Pi_t^r - P_t \tau_t \tag{3}$$

$$N_t = (1-\rho)N_{t-1} + p_t \left[L_t - (1-\rho)N_{t-1} \right] \tag{4}$$

Total labor income is given by $w_t N_t$ and unemployed household members receive unemployment benefits b_t, which evolve according to the stochastic process $ln(b_t) = \zeta^b ln(b_{t-1}) + (1 - \zeta^b) ln(b) + \epsilon_t^b$. Households receive profits Π_t^r from the monopolistic sector and invest in risk-free bonds that promise a unit of currency tomorrow and cost $(1+I_t)^{-1}$. They also have to pay lump-sum taxes τ_t in order to finance the unemployment insurance system. The final consumption good $C_t \equiv \int_0^1 \left[C_t(z)^{\frac{\varepsilon-1}{\varepsilon}} dz \right]^{\frac{\varepsilon}{\varepsilon-1}}$ is a Dixit-Stiglitz aggregator of the different varieties of goods produced by the retail sector and ε is the elasticity of substitution between the different varieties. The optimal allocation of income on each variety is given by $C_t(z) = \left[\frac{P_t(z)}{P_t} \right]^{-\varepsilon} C_t$, where $P_t = \left[\int_0^1 P_t(z)^{\frac{\varepsilon-1}{\varepsilon}} dj\right]^{\varepsilon/(1-\varepsilon)}$ is the price index. ε_t^p is an exogenous premium in the return to bonds which follows the stochastic process $ln(\varepsilon_t^p) = \zeta^p ln(\varepsilon_{t-1}^p) + (1-\zeta^p) ln(\varepsilon^p) + \epsilon_t^p$.

We obtain two equations describing the household's optimal consumption path and its participation decision

$$\beta\varepsilon_t^p E_t \frac{1+I_t}{\Pi_{t+1}} \left(\frac{\lambda_{t+1}}{\lambda_t}\right) = 1 \tag{5}$$

$$\chi_t L_t^{\varphi} C_t^{\sigma} = (1-p_t)b_t + p_t \left[w_t + E_t \beta_{t+1}(1-\rho)\left(\frac{1-p_{t+1}}{p_{t+1}}\right)\left(\chi_{t+1} L_{t+1}^{\varphi} C_{t+1}^{\sigma} - b_{t+1}\right)\right] \tag{6}$$

where $\lambda_t = C_t^{-\sigma}$ is the marginal utility of consumption and $\beta_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma}$ is the stochastic discount factor of the household. Equation (6) states that the marginal disutility of allocating an extra household member to participation, expressed in consumption units, has to be equal to the expected benefits of participating. The latter consist of unemployment benefits in case job search is unsuccessful and the wage plus the continuation value of being employed in case job search is successful. This equation makes clear that participation decisions depend on the relative strength of two effects. According to a wealth effect, when consumption increases, leisure becomes relatively more attractive and the desired size of the labor force decreases. According to a substitution effect, when wages and the job finding rate increase, market activity becomes relatively more attractive and the desired size of the labor force increases.

2.3 Firms

The economy consists of two sectors of production as in Trigari (2009) and Walsh (2005). Firms in the wholesale sector produce an intermediate homogeneous good in competitive markets using labor. Their output is sold to the final good sector (retailers) who are monopolistically competitive and transform the homogeneous goods one for one into differentiated goods at no extra-cost and apply a mark-up. Firms in the retail sector are subject to nominal price staggering.

2.3.1 Wholesale firms (intermediate goods sector)

Firms produce according to the following technology

$$Y_{jt}^w = Z_t N_{jt} \tag{7}$$

where Z_t is a common, aggregate productivity disturbance. Posting a vacancy comes a cost κ. Firm j chooses its level of employment N_{jt} and the number of vacancies v_{jt} in order to maximize the expected sum of its discounted profits

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left[\frac{P_t^w}{P_t} Y_{jt}^w - \kappa v_{jt} - w_t N_{jt}\right] \tag{8}$$

subject to its perceived law of motion of employment $N_{jt} = (1-\rho)N_{jt-1} + v_{jt} q(\theta_t)$ and taking as given the wage schedule. Wholesale firms sell their output in a competitive market at a price P_t^w. We define $\mu_t = \frac{P_t}{P_t^w}$ as the markup of retail over wholesale prices. The second and third terms in equation (8) are, respectively, the cost of posting vacancies and the wage bill. In equilibrium all firms will post the same number of vacancies and we can therefore drop individual firm subscripts j. We obtain the following job creation equation

$$\frac{\kappa}{q(\theta_t)} = \frac{Z_t}{\mu_t} - w_t + E_t\beta_{t+1}(1-\rho)\frac{\kappa}{q(\theta_{t+1})} \tag{9}$$

This equation is an arbitrage condition for the posting of vacancies. It states that the cost of posting a vacancy, the deadweight cost κ divided by the time it takes to fill the vacancy, must be equal to the expected discounted benefit of a filled vacancy. These benefits consist of the revenues from output net of wages and the future savings on vacancy posting costs.

2.3.2 Wages

In order to characterize the outcome of wage negotiations, we must first define the value of the marginal worker for the firm and the value of the marginal employed individual for the household. The value of the marginal worker for the firm is

$$J_t = \frac{Z_t}{\mu_t} - w_t + E_t\beta_{t+1}(1-\rho)J_{t+1}$$

Consider the household's welfare criterion

$$H_t(N_t) = Max_{C_t,B_{t+1},N_t,L_t}\left\{\frac{C_t^{1-\sigma}}{1-\sigma} - \chi_t\frac{L_t^{1+\varphi}}{1+\varphi} + \beta E_t H_{t+1}(N_{t+1})\right\}$$

It follows that

$$\frac{\partial H_t(N_t)}{\partial N_t} = C_t^{-\sigma}(w_t - b_t) + E_t\beta(1-\rho)(1-p_{t+1})\frac{\partial H_{t+1}(N_{t+1})}{\partial N_{t+1}}$$

The value to the household of the marginal employed individual is $W_t - U_t = \frac{\frac{\partial H_t(N_t)}{\partial N_t}}{C_t^{-\sigma}}$

$$W_t - U_t = w_t - b_t + E_t\beta_{t+1}(1-\rho)(1-p_{t+1})(W_{t+1} - U_{t+1})$$

If we compare this equation with equation (6), we can see that $W_t - U_t = \frac{1}{p_t}\left(\frac{\chi_t L_t^{\varphi}}{C_t^{-\sigma}} - b_t\right)$. Wages are then determined through a Nash bargaining scheme between workers and employers who maximize the joint surplus of employment by choosing real wages

$$argmax_{\{w_t\}}\left[(J_t)^{1-\eta_t}(W_t - U_t)^{\eta_t}\right] \tag{10}$$

where η_t is the worker's bargaining power. It evolves exogenously according to $\eta_t = \eta\varepsilon_t^{\eta}$ where ε_t^{η} is a bargaining power shock that follows the stochastic process $ln(\varepsilon_t^{\eta}) = \zeta^{\eta}ln(\varepsilon_{t-1}^{\eta}) + (1-\zeta^{\eta})ln(\varepsilon^{\eta}) + \epsilon_t^{\eta}$. We obtain the following sharing rule

$$(1-\eta_t)(W_t - U_t) = \eta_t J_t \tag{11}$$

After some algebra, we find

$$w_t = b_t + \frac{\eta_t}{1-\eta_t}\frac{\kappa}{q(\theta_t)} - E_t\beta_{t+1}(1-\rho)(1-p_{t+1})\frac{\eta_{t+1}}{1-\eta_{t+1}}\frac{\kappa}{q(\theta_{t+1})} \tag{12}$$

2.3.3 Retail firms

A measure one of monopolistic retailers produces differentiated goods with identical technology transforming one unit of intermediate good into one unit of differentiated retail good. The demand function for retailer's products is

$$Y_t(z) = (P_t(z)/P_t)^{-\epsilon} Y_t^d \tag{13}$$

where $P_t = \left[\int_0^1 P_t(z)^{1-\epsilon}\right]^{1/(1-\epsilon)}$ and Y_t^d is aggregate demand for the final consumption good. As in Calvo (1983), we assume that each retailer can reset its price with a fixed probability $1-\delta$ that is independent of the time elapsed since the last price adjustment. This assumption implies that prices are fixed on average for $\frac{1}{1-\delta}$ periods. Retailers choose optimally their price $P_t^o(z)$ to maximize expected future discounted profits given the demand for the good they produce and under the hypothesis that the price they set at date t applies at date $t+s$ with probability δ^s.

$$MaxE_t \sum_{s=0}^{\infty}(\delta^s \beta_{t,t+s}\left[\frac{P_t^o(z) - P_{t,t+s}^w}{P_{t,t+s}}\right] Y_{t,t+s}(z))$$

All firms resetting prices in any given period choose the same price. The aggregate price dynamics is then given by

$$P_t = \left[\delta P_{t-1}^{\varepsilon} + (1-\delta)\left(P_t^o\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}$$

2.4 Resource constraint and Monetary Policy

The government runs a balanced budget. Lump-sum taxation is used to finance the unemployment insurance system $b_t(1-p_t)s_t = \tau_t$. Aggregating equation (13) across firms, we obtain

$$Y_t = Z_t N_t = \int_0^1 \left(\frac{P_t(z)}{P_t}\right)^{-\varepsilon}\left[C_t + \kappa v_t\right] dz \tag{14}$$

where $\int_0^1 \left(\frac{P_t(z)}{P_t}\right)^{-\varepsilon}$ measures relative price dispersion across retail firms. Monetary policy is assumed to be conducted according to an interest rate reaction function of the form

$$log\left(\frac{1+I_t}{1+I}\right) = \phi_r log\left(\frac{1+I_{t-1}}{1+I}\right) + (1-\phi_r)\left(\phi_\pi log\left(\frac{\Pi_t}{\Pi}\right) + \phi_y log\left(\frac{Y_t}{Y}\right)\right) \tag{15}$$

The log-linear equations characterizing the decentralized equilibrium are presented in Appendix A.1.

3 Robust Sign Restrictions

3.1 Methodology

We calibrate the model to study the effects of four different shocks. Two labor market shocks, a labor supply shock and a wage bargaining shock are considered alongside standard demand and neutral technology shocks. In Section 6 we extend our analysis and study the effects of matching efficiency and unemployment benefits shocks whereas price mark-up shocks are considered in Appendix 4. The labor supply shock is captured by the preference shifter χ_t in equation (6). A decrease in χ_t lowers the disutility of allocating an extra household member to labor force participation and, all other things being equal, leads to an increase in the desired size of the labor force. The wage bargaining and the neutral technology shocks show up respectively, as variations in the share of the surplus associated with an employment relationship that accrues to the household, η_t in equation (11), and as movements in Z_t in equation (7). The demand shock is modelled through a "risk-premium" shock ε_t^p, which drives a wedge between the interest rate controlled by the central bank and the return on assets held by the households. As explained in Fisher (2014), this term can be interpreted as a structural shock to the demand for safe and liquid assets such as short-term US Treasury securities. A positive shock to ε_t^p increase household's incentives to save and reduces current consumption. However, our identified demand shock should not only be interpreted in this narrow sense since the restrictions that we impose in section 3.3 are also consistent with other demand disturbances such as monetary policy, government spending and discount factor shocks.

We use the theoretical model to derive sign restrictions that are robust to parameter uncertainty. In order to do so, we follow the approach outlined in Peersman and Straub (2009) and Pappa (2009) and assume that the values of key parameters are uniformly and independently distributed over a selected range. This range for each structural parameter is chosen by conducting a survey of the empirical literature. We then draw a random value for each parameter and compute the distribution of impact responses to a given shock for each variable of interest. This exercise is repeated for 10,000 simulations. Note that it is common practice in the literature to only show percentiles of the distribution of theoretical impulse response functions. We choose to report the entire distribution in order to ensure the robustness of our sign restrictions.

3.2 Parameter ranges

The model period is one quarter. Some parameters are fixed to a particular value. The discount factor is set to 0.99, so that the annual interest rate equals 4%. The steady-state labor force participation rate is set to 0.66, its pre-crisis level. We set the steady state levels of tightness and unemployment to their mean values over the period 1985-2014. We use the seasonally-adjusted monthly unemployment rate constructed by the Bureau of Labor Statistics (BLS) from the Current Population Survey (CPS). Labor market tightness is computed as the ratio of a measure of the vacancy level to the seasonally-adjusted monthly unemployment level constructed by the BLS from the CPS. The measure of the vacancy level is constructed by using the Conference Board help-wanted advertisement index for 1985-1994, the composite help-wanted index of Barnichon (2010) for 1995-2014 and the seasonally-adjusted monthly vacancy level constructed by the BLS from JOLTS for 2001-2014. Over these periods, the mean of the unemployment rate is 6.1% and the mean of labor market tightness is 0.5. For practical purposes, our targets will be 6% and 0.5 respectively. We follow Blanchard and Gali (2010) and assume that the steady state job finding rate is equal to 0.7. These targets imply, through the Beveridge Curve, a job destruction rate of approximately 0.15. The staying rate ω is set to 0.22, its mean in the data over the period 1990-2013 (see Hornstein 2013).

The intervals for the other parameters are chosen according to the results of empirical studies and to the posterior distribution of structural parameters reported in estimated medium-scale DSGE models. The coefficient of risk-aversion σ is allowed to vary in the interval $[1, 3]$, the preference parameter φ driving the disutility of labor supply in the interval $[1, 5]$, and the degree of price stickiness δ in the interval $[0.5, 0.8]$. The elasticity of substitution between goods ε is assumed to vary in the interval $[6, 11]$, which corresponds to a steady-state markup between 10 and 20 percent . The elasticity of matches with respect to the number of job seekers α is allowed to vary in the interval $[0.5, 0.7]$, following evidence in Petrongolo and Pissarides (2000). The replacement ratio b/w is assumed to lie in the interval $[0.2, 0.6]$, which is centered around the value used by Shimer (2005) and comprises the ratio of benefits paid to previous earnings of 0.25 used by Hall and Milgrom (2008). Following evidence in Silva and Toledo (2009), the vacancy posting cost κ is fixed such that hiring costs are comprised between 4 and 14 percent of quarterly compensation. The steady state values of the matching efficiency parameter Γ, the bargaining power η and the parameter scaling the disutility of participating χ are then determined through steady-state relationships.

For the monetary policy rule, we choose ranges that include parameter values generally discussed in the literature. We restrict the inflation response to the range $[1.5, 3]$, the output response to the range $[0, 1]$, and the degree of interest rate smoothing to the range $[0, 1]$. The intervals for the persistence of the different shocks are chosen according to the posterior distributions of parameters reported in the estimated DSGE models of Galí, Smets and Wouters (2011), Gertler, Sala and Trigari (2008), Sala, Söderström and Trigari (2008) and Furlanetto and Groshenny (2013). Table 1 gives the ranges for all the parameters.

Table 1: Parameter Ranges

Parameter	Description	Range
σ	Coefficient of risk aversion	[1,3]
φ	Inverse of the Frisch labor supply elasticity	[1,5]
δ	Degree of price stickiness	[0.5,0.8]
ε	Elasticity of substitution between goods	[6,11]
α	Elasticity of matches with respect to s	[0.5,0.7]
$\frac{b}{w}$	Replacement ratio	[0.2,0.6]
$\frac{\kappa}{q}$	Hiring costs (as a % of quarterly wages)	[4,14]
ϕ_r	Interest rate inertia	[0,0.9]
ϕ_π	Interest rate reaction to inflation	[1.5,3]
ϕ_y	Interest rate reaction to output	[0,1]
ζ^p	Autoregressive coefficient, risk-premium shock	[0.1,0.8]
ζ^z	Autoregressive coefficient, neutral technology shock	[0.5,0.99]
ζ^χ	Autoregressive coefficient, labor supply shock	[0.5,0.99]
ζ^η	Autoregressive coefficient, bargaining shock	[0,0.5]
ζ^γ	Autoregressive coefficient, matching efficiency shock	[0.5,0.99]
ζ^b	Autoregressive coefficient, unemployment benefits shock	[0.5,0.99]

3.3 Impact Responses to Shocks and Sign Restrictions

We now proceed to the simulation exercise. All the shocks we consider increase output contemporaneously. Figure 1 shows that a negative risk-premium shock triggers a positive response of output and prices. As the premium on safe assets decreases, it becomes less interesting for households to save and aggregate demand increases. Firms would like to increase prices but most are unable to do so and need to respond to the higher demand by producing more. In order to do so, they recruit more workers and unemployment decreases. These positive responses of output and prices and the negative response of unemployment will be used as sign restrictions in the VAR to identify demand shocks. The restriction on prices is especially important as it enables us to disentangle demand shocks from other shocks.

The distribution of impact responses to technology shocks is presented in Figure 2. Positive technology shocks lead to a decrease in marginal costs and prices. The reactions of unemployment and vacancies depend on the degree of price stickiness and on the response of monetary policy. Firms can now produce more with the same number of employees and they would like to decrease prices and increase production. However, most of them are unable to do so and contract employment by reducing the number of vacancies. This effect is stronger the higher the degree of price stickiness and the weaker the response of monetary policy following the shock. When the central bank responds vigorously to inflation and mildly to the output gap, the large decrease in the real interest rate counteracts this effect. Importantly, in the event of a strong drop in vacancies and of a rise in unemployment (which happens when prices are very rigid and monetary policy is very inertial), the decrease in hiring costs may lead to a decrease in wages on impact. However, wages overshoot their steady-state value under all parameter configurations from period two onwards. We use the positive response of output and wages and the negative response of prices to identify technology shocks.[4]

The distribution of impact responses to labor supply shocks is presented in Figure 3. Positive labor supply shocks take the form of a decrease in the disutility of allocating an extra household member to participation. It becomes beneficial for households to allocate more of their members to job search and labor force participation increases. This increase in the number of job seekers makes it easier for firms to fill vacancies and hiring costs decrease, thereby leading to a decrease in wages and prices and to an increase in output and employment. However, all new participants do not find a job immediately and unemployment increases in the first periods after the shock. We use the positive responses of output and unemployment and the negative responses of wages and prices to identify labor supply shocks. As in Peersman and Straub (2009), which derive a set of sign restrictions from a standard New Keynesian model, the asymmetric behavior of wages in response to labor supply shocks and technology shocks is key in identifying these two forces.

The distribution of impact responses to a wage bargaining shock is presented in Figure 4. This shock has a direct negative effect on wages. This contributes to lower marginal costs and prices. Because firms now capture a larger share of the surplus associated with employment relationships, they post more vacancies and increase employment. In spite of the higher job finding rate, the increase in consumption and the decrease in wages tend to lower participation. Unemployment unambiguously decreases. We use the positive response of output and the negative responses of wages, prices and unemployment to identify wage bargaining shocks. Note that the sign restrictions we use to identify this shock are also consistent with two other labor market shocks, a matching efficiency shock and an unemployment benefits shock. To account for this issue, we further disentangle the wage bargaining shock in Section 6. Table 2 provides a summary of the sign restrictions.

Table 2: Sign restrictions

	Demand	Technology	Labor supply	Wage bargaining
GDP	+	+	+	+
Prices	+	-	-	-
Wages	/	+	-	-
Unemployment	-	/	+	-

The main contribution of this paper is to use unemployment data to separately identify labor supply shocks from other labor market shocks within the context of a VAR model. It is the restriction on unemployment that enables us to separately identify the labor supply shock and the wage bargaining shock. Importantly, our restrictions are not only robust to parameter uncertainty but also, to some extent, to model uncertainty. Indeed, all the restrictions we impose are also satisfied in the model developed by Galí, Smets and Wouters (2011) in which

[4]In the baseline exercise, the restriction on wages is imposed on impact. In Section 4.2 we check that imposing the restriction in period two (rather than on impact) does not alter the results

unemployment arises from the monopoly power of unions and preferences feature a very low wealth effect. In that model, labor force participation and unemployment are also procyclical in response to labor supply shocks and countercyclical in response to wage-markup shocks. A positive labor supply shock leads to an increase in the size of the labor force and, because wages do not adjust immediately to maintain wage-markups constant, to an increase in unemployment. A negative wage-markup shock leads to a decrease in wages and unemployment. As a result labor force particpation, which is directly linked to the level of wages, also decreases.

Notice that the sign of the unemployment response is sufficient to disentangle the labor market shocks. Nonetheless, the participation response (procyclical to labor supply and countercyclical to wage bargaining) can help in refining the identification. We will explore this avenue in an extension in Section 5.

Our VAR identification scheme is related also to earlier attempts to identify labor supply disturbances in the sign restrictions literature. Peersman and Straub (2009) identify demand and technology shocks alongside labor supply shocks by using a sign-restricted VAR. We go one step further in that we manage to separately identify labor supply shocks from other labor market shocks. Chang and Schorfheide (2003) assume that an increase in hours due to a labor supply shock leads to a fall in labor productivity as the productive capacity of the economy is fixed in the short-run. As they note, their identified labor supply shock might also correspond to a demand shock. In the presence of sticky prices, an exogenous increase in demand also generates a negative co-movement between hours and labor productivity. We are able to circumvent this problem with our identification scheme.

4 Empirical Results

In this section we present the results derived from our baseline model that is estimated with Bayesian methods with quarterly data in levels from 1985Q1 to 2014Q1 for the US. The VAR includes five lags and four endogenous variables, i.e. GDP, the GDP deflator as a measure of prices, real wages and the unemployment rate. All variables with the exception of the unemployment rate are expressed in terms of natural logs. The data series are described in Appendix 2 whereas the details of the econometric model and its estimation are presented in Appendix 3. The baseline model includes four shocks: one demand shock and three supply shocks (a technology shock, a labor supply shock and a wage bargaining shock).

4.1 The Baseline VAR model

Figure 5 plots the variance decomposition derived from our model. The horizontal axis represents the horizon (from 1 to 35 quarters) and the vertical axis represents the share of the variance of a given variable explained by each of the four shocks. The variance decomposition is based at each horizon on the median draw that satisfies our sign restrictions.

The main result that emerges from our analysis is that both our identified labor market shocks play a significant role in explaining economic fluctuations. These shocks account for 20 percent of output fluctuations on impact and almost 80 percent in the long-run. Moreover, they explain around 50 percent of unemployment fluctuations at short horizons and 80 percent at long horizons. The wage bargaining shock is more important at short horizons (especially for unemployment) whereas the labor supply shock is crucial to capture macroeconomic dynamics at low frequencies (both for output and unemployment). In Figures 6 and 7 we present the impulse response functions for these two labor market shocks. The labor supply shock has large and persistent effects on GDP. The decline in real wages is protracted despite the fact that we impose the restriction only on impact. This is key to separately identify labor supply and technology shocks. The median response of unemployment is positive for the first three quarters before turning negative. Thus, the adverse unemployment effects of a positive labor supply disturbance are rather short-lived. An expansionary wage bargaining shock has a large and persistent effect on the unemployment rate, which declines for several quarters, and to some extent also on output. Notice that at this stage the only source of identification between the labor market shocks is the behavior of unemployment in the very short-run. Nevertheless, this restriction turns out to be sufficiently informative so that the model assigns a larger explanatory power to labor supply shocks in the long-run, a feature that, we believe, is realistic.

An important role for shocks originating in the labor market in driving economic fluctuations is in keeping with results from previous VAR studies that include labor supply shocks (without, however, disentangling wage mark-up shocks). In Shapiro and Watson (1988) the labor market shock explain on average 40 percent of output fluctuations across different horizons and 60 percent of short term fluctuations in hours (80 per cent in the long run). In Chang and Schorfheide (2003) labor-supply shifts account for about 30 percent of the variation in hours and about 15 percent of the output fluctuations at business cycle frequencies. Peersman and Straub (2009) do not report the full variance decomposition in their VAR but the limited role of technology shocks in their model let us conjecture an important role for the two remaining shocks, i.e. demand and labor supply. We conclude that the available VAR evidence is reinforced by our results. While the structural interpretation of our identified labor supply and wage bargaining shocks remains an open question, our model suggests that supply shocks that move output and real wages in opposite directions (and with different impact effects on unemployment) play a key role in macroeconomic dynamics.

Our results are also related to previous theoretical studies in the business cycles literature dealing with the importance of shocks originating in the labor market. Hall (1997) identified preference shifts as the most important driving force of changes in total working hours. In the DSGE literature, this preference shift, or "labor wedge" in the terminology of Chari, Kehoe and McGrattan (2009), has been interpreted either as an efficient shock to preferences or as an inefficient wage mark-up shock (Smets and Wouters, 2007). Because these two shocks are observationally equivalent in a standard New Keynesian model, several authors have attempted to disentangle them by imposing additional assumptions. In Justiniano, Primiceri and Tambalotti (2013), wage markup shocks are assumed to be white noise and their explanatory power is concentrated in the very short run, whereas labor supply shocks are key drivers of macroeconomic fluctuations.[5] Galí, Smets and Wouters (2011) are able to disentangle the two shocks but in their model unemployment is solely due to the monopoly power of households or unions in labor markets. Thus, long-run movements in unemployment can only be driven by wage

[5]The role of wage mark-up shocks is reduced further by the introduction of a measurement error in wages that makes these shocks irrelevant for business cycle fluctuations. The presence of this measurement error differentiates Justiniano, Primiceri and Tambalotti (2013) from Smets and Wouters (2003).

markup shocks. Not surprisingly, they find that wage markup shocks account for 80 to 90% of unemployment fluctuations at a 40 quarters horizon. Our findings suggest that shocks generating the type of co-movements between variables that are typically associated with wage-markup shocks are important *both* in the short run *and* in the long-run. Moreover, they are not the only driving force of unemployment in the long-run. Thus, we do not find support for the polar assumptions about the role of wage-markup shocks made in the aforementioned papers. We do, however, provide an alternative way of solving the observational equivalence problem between wage bargaining and labor supply shocks within the context of a New Keynesian model. In the theoretical framework of section 2, labor supply shocks and wage bargaining shocks appear in different equations (equations 6 and 12, respectively) and can be separately identified without imposing additional assumptions.

While we concentrate our interest on the labor market shocks, our baseline model also includes demand shocks and technology shocks whose impulse responses are presented in Figures 8 and 9. We find that demand shocks are the main drivers of fluctuations in prices both in the short and in the long run, as in Furlanetto, Ravazzolo and Sarferaz (2014). They also play a substantial role for output and unemployment fluctuations at short horizons. Technology shocks are the dominant drivers of real wages, thus suggesting a tight link between real wages and productivity.[6] The response of real wages to demand shocks and the response of unemployment to technology shocks are left unrestricted in our identification scheme. Therefore, the model may provide some genuine empirical evidence on these issues that have been discussed in depth in the theoretical literature (cf. Galí, 1999 and 2013). In our model real wages tend to decrease in response to an expansionary demand shock. This is consistent with the predictions of a New Keynesian model with a moderate degree of price rigidity and an important degree of wage stickiness (Galí, 2013). Additionally, we find that unemployment decreases in response to a positive technology shock. This is consistent with New Keynesian models with a limited degree of price stickiness and a not too inertial monetary policy rule and with previous evidence in the sign restrictions literature (cf. Peersman and Straub, 2009) but is in contrast with the evidence presented in most VAR models identified with long-run restrictions (cf. Galí, 1999).

4.2 Sensitivity Analysis

We now test the robustness of our results with respect to the choice of the sample period, the wage series included in the estimation and the measure of central tendency used to compute the variance decomposition. In Figure 10 we present the variance decomposition for output and unemployment in each experiment.

In the first row we expand the sample period by using data over 1965Q1-2014Q1. As in the baseline model, wage bargaining shocks are more important for unemployment whereas labor supply shocks matter more for output. Nonetheless, once again polar assumption on the role of the two labor market shocks are not supported by the VAR. More generally, the joint importance of the two labor market shocks is lower than in the baseline model.

[6] In our empirical model productivity shocks have a large effect on real wages and a limited effect on unemployment. This is consistent with most models with search and matching frictions driven only by productivity shocks. According to our results, those models should not be dismissed simply because they generate limited unemployment volatility in response to technology shocks. The bulk of unemployment volatility may be explained by other shocks.

In the second row we restrict our attention to the Great Moderation period (1985Q1-2008Q1), thus excluding the Great Recession from the sample period. We see that the relative importance of labor supply and wage bargaining shocks is confirmed (in particular for unemployment dynamics) whereas their joint importance for business cycle fluctuations is reduced. This indicates that the model sees the Great Recession as a period of unusually large labor market shocks.

We then estimate the baseline model over the baseline sample period including a different wage series in the set of observable variables (cf. third row in Figure 10). Following Justiniano, Primiceri and Tambalotti (2013) we use data on nominal compensation per hour in the nonfarm business sector, from NIPA. This series is more volatile than the BLS series that we use in our baseline analysis. Both series can be seen as imperfect measures of our model-based wage concept. In this case the importance of wage bargaining shocks increases substantially.

In our baseline model we follow the early sign restriction literature and show variance decompositions that are based at each horizon on the median draw that satisfies our restrictions. We now also present results based on different measures of central tendency such as the median target proposed by Fry and Pagan (2011).[7] In this experiment (cf. fourth row in Figure 10) the importance of labor supply shocks for GDP is slightly larger than in our baseline model whereas results for unemployment are largely confirmed.

Finally, in the last row of Figure 10 we reconsider the restriction imposed on the response of real wages to technology shocks. In our theoretical model the impact response can be negative for extreme parameterizations characterized by a high degree of price stickiness and interest rate smoothing. However, the response of real wages is unambiguously positive at horizon two. In our last sensitivity check we take the model at face value and we impose the restriction on real wages at quarter two rather than on impact. The results are basically unaffected.

To sum up, we conclude that the relative importance of the two labor market shocks is robust across the different experiments (with a larger role for wage bargaining shocks in the short term and a larger role for labor supply shocks in the long run) whereas the joint role of the two labor market shocks is somewhat lower (although still far from being negligible) when we extend or reduce the sample period.

5 Introducing data on the participation rate

In the previous section we have identified labor supply and wage bargaining shocks on the basis of the different sign of the unemployment response. In this section we further disentangle the two shocks by using data on the labor force participation rate. A robust feature of our theoretical model is that the participation rate is procyclical in response to labor supply shocks and countercyclical in response to wage bargaining shocks. A decrease in the bargaining power of workers triggers a decrease in wages and an increase in consumption, which tend to make participation relatively less attractive, and an increase in the job-finding rate, which tends to make participation relatively more attractive. The first two effects dominate in most of the parameterizations of the model we consider (cf Figure 4). This restriction is also satisfied in the

[7] Fry and Pagan (2011) show that it is problematic to interpret structurally the median of sign-restricted impulse responses. In fact, taking the median across all possible draws at each horizon implies mixing impulse responses that emanate from different structural models. They suggest choosing impulse responses from the closest model to the median response instead.

estimated New Keynesian of Galí, Smets and Wouters (2011) which features preferences with a low wealth effect on labor supply and sticky wages.

We introduce the participation rate in the VAR to take advantage of the additional restrictions. We include also a fifth shock with no specific economic interpretation that is defined as a residual shock that does not satisfy the restrictions imposed on the other four identified shocks. In that way we match the number of shocks and the number of variables in the system.[8] The restrictions are summarized in Table 3.

Table 3: Sensitivity analysis: Sign restrictions

	Demand	Technology	Labor supply	Wage bargaining
GDP	+	+	+	+
Prices	+	-	-	-
Wages	/	+	-	-
Unemployment	-	/	+	-
Participation	/	/	+	-

In Figure 11 we plot the variance decomposition for the extended model with five shocks. We remark that the previous results for output and unemployment are broadly confirmed: if anything, we see a slightly larger role for wage bargaining shocks on the decomposition for GDP, thus making the contribution of the two labor market shocks more balanced. The residual shock plays a minor role except for prices and, to some extent, for real wages. It is confirmed that demand and technology shocks are the dominant drivers of prices and real wages respectively.

The participation rate is mainly driven by labor supply shocks, both in the short run and in the long run. The contribution of wage bargaining shocks is relevant in the short-run whereas demand and technology shocks have a limited effect. In Figure 12 we plot the impulse responses of the participation rate to the four identified shocks.[9] An expansionary labor supply shock has a very persistent effect on the participation rate whereas the impact of a wage bargaining shock is more short-lived (negative over the first three quarters and positive afterwards). The participation rate does not respond to demand shocks whereas it tends to increase in response to technology shocks (although the impact response is uncertain).[10]

Our model can also be used to investigate the historical evolution of the participation rate, with a special interest over the recent years. It is well known that the participation rate has been steadily increasing over time until the very end of the 90s. Since then, it has been gently declining with an acceleration from 2008 onwards (cf. the solid line in Figure 13 where the

[8]An alternative set-up that include a fifth shock with economic interpretation is considered in Appendix 4. There we consider price mark-up shocks by introducing additional restrictions on the behavior of the particpation rate.

[9]The impulse-responses for the other variables are very similar to the ones derived in the baseline model. They are available upon request.

[10]The evidence on the response of participation to technology shocks is mixed. Gali (2011) and Christiano et al. (2012) both identify technology shocks using long-run restrictions and come up with different results. The exact specification of their models differ in that Christiano et al. (2012) include more variables in their analysis and identify more shocks. Our results, which are obtained using sign-restrictions, are consistent with the evidence presented in the latter paper.

participation rate is plotted in deviation from its mean over the sample period). In the absence of shocks the model would forecast the participation rate at the end of the sample to be 1 percent above its sample mean rather than 3 percent below. The model interprets the recent decline in the participation rate as driven mainly by contractionary labor supply shocks which explain around half of the recent decline. Wage bargaining and demand shocks each account for roughly one fourth of the decline whereas technology shocks are almost irrelevant in driving participation dynamics.

Our results complement a recent and rich literature on the decline in participation that is summarized in Bullard (2014). One strand of the literature interprets the decline in participation as a response to the protracted weak state of the economy (cf. Erceg and Levin, 2014; Daly and Valletta, 2014; among others). Under this view (”the bad omen view” in the words of Bullard, 2014) the decline of the unemployment rate over the last period does not really reflect an improvement in the labor market because it coexists with a stubbornly low employment to population ratio. In contrast, a second strand of the literature argues that the decline in the participation rate simply reflects changing demographics in the US economy, and that the different demographics groups have different propensities to participate (cf. Fujita, 2013; Kudlyak, 2014; among others). Under this view (the ”demographics view” in the words of Bullard, 2014), the unemployment rate remains a good indicator of labor market health. Our labor supply shock explain slightly more than 50 percent of the participation decline and may capture, at least to some extent, ”the demographics view”. Our results are then in the ballpark of BLS projections (according to which more than 70 percent of the decline is due to pure demographic factors) and of Fujita (2014) who finds that about 65 percent of the decline in participation is due to retirements and disability.

However, our labor supply shocks are also likely to capture a declining desire to work in addition to the demographic factors. Supporting evidence is provided in a recent paper by Barnichon and Figura (2014) who use CPS micro data and a stock-flow accounting framework to explain the downward trends in unemployment (between the early 1980s and the early 2000s) and in participation (since the beginning of the 2000s). Barnichon and Figura (2014) identify a secular decline in the share of non-participants who want a job and, importantly, this decline is broad-based across demographic groups. Non-participants interested in a job usually enter the labor force only rarely and mainly directly through employment. Therefore, a decline in their share may lower both the unemployment rate and the participation rate. This labor supply shift can account for 1.75 percentage points of the decline in participation, whereas the demographic factors account for additional 1.5 percentage points. Barnichon and Figura (2014) suggest three possible explanations for this negative labor supply shift: i) a reduction in the added-worker effect driven by the strong wage growth in second half of the 90s, ii) a higher emphasis on education, perhaps in part in response to a rising high school and college wage premium, iii) a change in preferences. All these factors are likely to be captured by our labor supply shock together with the demographic factors.

6 Disentangling wage bargaining shocks

In the previous sections we have shown that labor supply and wage bargaining shocks can be separately identified on the basis of the unemployment and participation rate responses to shocks. As we have seen in the previous section, the use of data on participation is particularly useful to refine the interpretation of labor supply shocks. The objective of this section is to disentangle further the wage bargaining shock. In particular, we rely again on our theoretical model presented in Section 2 to show that the dynamics generated by wage bargaining shocks are similar to the ones derived from shocks to unemployment benefits and matching efficiency.

In Figure 14 we plot the distribution of impact responses to an unemployment benefit shock, i.e a variation in b_t in equation (12). We see that the impact effects on all the variables are the same as the ones generated by wage bargaining shocks. Therefore, exogenous variations in unemployment benefits are captured by wage bargaining shocks in the VAR. In Figure 15 we plot the distribution of impact responses to a matching efficiency shock that shows up as a variation in the parameter γ in the matching function (for an extensive analysis on the properties and the interpretation of shocks to matching efficiency, cf. Furlanetto and Groshenny, 2014). The sign of the responses of output, prices, unemployment, real wages and participation rate are the same in response to both matching efficiency shocks and wage bargaining shocks. Therefore, we can conclude that the wage bargaining shock identified in the VAR should not be interpreted narrowly as just reflecting fluctuations in the bargaining power of workers. It captures also fluctuations in unemployment benefits and variations in matching efficiency.

While in the baseline VAR model matching efficiency shocks are grouped together with wage bargaining shocks, the use of data on vacancies may allow us to separately identify the two shocks. An improvement in matching technology lowers hiring costs and wages. As vacancies are filled more easily, firms expand employment and output increases. The sign of the response of vacancies depends crucially on the degree of price stickiness (cf. Furlanetto and Groshenny, 2014). Under sticky prices, firms do not decrease prices as much as they would like to and the expansion in aggregate demand is less pronounced. Thus firms do not need to post vacancies to produce the quantities demanded. As a matter of fact, from period two onwards, they actually post fewer vacancies.[11] This result holds for even moderate degrees of price stickiness. The distribution of impact responses to a matching efficiency shock is presented in Figure 15. In contrast wage bargaining shocks move unemployment and vacancies in opposite directions as it can be seen in Figure 4.

We can go one step further in the analysis by introducing data on vacancies in our VAR and by using the asymmetric response of this variable in response to wage bargaining and matching efficiency shocks to disentangle these two forces.[12] In Figure 16, we plot the variance decomposition of this extended model. While the contribution of demand and technology shocks to economic volatility is mostly unchanged, labor supply and wage bargaining shocks now account for a more modest share of fluctuations in output and unemployment. The contribution of the matching efficiency shock to the variance of the different variables is substantial. In Figure 17

[11] Benati and Lubik (2014) show that separation rate shocks also move unemployment and vacancies in the same direction.

[12] The restriction on vacancies is imposed on impact for the wage bargaining shock and in the second period for the matching efficiency shock in keeping with the analysis carried out in the theoretical model.

we see that two shocks can be interpreted as shifters of the Beveridge curve insofar as they move unemployment and vacancies in the same direction on impact. This was imposed as an identification assumption for matching efficiency shocks but it emerges as a genuine feature of the data for labor supply shocks. Therefore, our analysis adds one additional element to the debate on the possible shift of the Beveridge curve in recent years: while a negative matching efficiency triggers an outward shift of the Beveridge curve, a negative labor supply shock generates an inward shift on impact. As far as we know, this dimension has been so far neglected in the debate.

7 Conclusion

We propose a new VAR identification scheme that enables us to separately identify different labor market shocks. Identification is achieved by imposing robust sign restrictions that are derived from a New Keynesian model with search and matching frictions in the labor market and endogenous labor force participation. Our key contribution is to use data on unemployment and labor force participation to disentangle labor supply shocks from wage bargaining shocks. We show that unemployment and participation are procyclical in response to a labor supply shock while they are countercyclical in response to a wage bargaining shock. Our model is estimated with Bayesian methods on U.S. data over the period 1985-2014. We find that both our identified labor market shocks are important drivers of output and unemployment fluctuations. The strength of wage bargaining shocks is greater in the short-run while labor supply shocks are crucial to capture macroeconomic dynamics at low frequencies. However, the two shocks have a quantitatively relevant impact both in the short-run and the long-run. We also study the recent behavior of the labor force participation rate in the U.S. through the lens of our model. We find that about half of the decline in participation during the recent recession can be accounted for by our identified labor supply shock.

We think that these two labor market shocks are likely to capture a broad series of factors. We show that the restrictions we impose to identify wage bargaining shocks are also compatible with unemployment benefits shocks and shifts in matching efficiency. Similarly, different interpretations may be attached to labor supply shocks. An interesting avenue for future research would be to disentangle the demographic explanation from the declining desire to work among non-participants, in particular by investigating the possible explanations proposed by Barnichon and Figura (2014).

References

[1] Arseneau, D., and S. Chugh, "Tax Smoothing in Frictional Labor Markets," Journal of Political Economy, 2012 vol. 120, 926-985

[2] Barnichon, R., "Building a Composite Help Wanted Index," Economics Letters, 2010, 175-178

[3] Barnichon, R. and A. Figura, "What Drives Movements in the Unemployment Rate? A Decomposition of the Beveridge Curve," FEDS Working Paper 2010-48

[4] Bullard, J., “The Rise and Fall of Labor Force Participation in the U.S.”, Speech at the Exchequer Club, Washington D.C.

[5] Campolmi, A. and S. Gnocchi, “Labor Market Participation, Unemployment and Monetary Policy,” Bank of Canada Working Paper 2014/9

[6] Canova, F. and G. De Nicolo’, ”Monetary Disturbancies Matter for Business Cycle Fluctiations in the G7”, Journal of Monetary Economics, vol. 49, 2002, 1131-1159

[7] Chang, Y. and F. Schorfheide, “Labor-Supply Shifts and Economic Fluctuations,” Journal of Monetary Economics, 2003, 1751-1768

[8] Chari, V., Kehoe P. and E. McGrattan, “New Keynesian Models: Not Yet Useful for Policy Analysis,” American Economic Journal: Macroeconomics, vol. 1(1), 2009, 242-266

[9] Christiano, L., Eichenbaum, M. and M. Trabandt, “Understanding the Great Recession,” Working Paper 2014

[10] Christiano, L., Trabandt, M. and K. Walentin, “Involuntary Unemployment and the Business Cycle,” Working Paper 2012

[11] Elsby, M., Hobijn, B. and A. Sahin, “On the Importance of the Participation Margin for Market Fluctuations,” Federal Reserve Bank of San Francisco Working Paper Series, 2013-05

[12] Ebell, M., “On the Cyclicality of Unemployment: Resurrecting the Participation Margin,” Labour Economics, 2011, 822-836

[13] Fry, R. and A. Pagan, ”Sign Restrictions in Structural Vector Autoregressions. A Critical Review,” Journal of Economic Literature, vol. 49, 2011, 938-960

[14] Fujita, S., “On the Causes of Declines in the Labor Force Participation Rate,” Research Rap Special Report, Federal Reserve Bank of Philadelphia, February 6, 2014

[15] Furlanetto, F. and N. Groshenny, “Matching Efficiency and Business Cycle Fluctuations,” Working Paper 2013

[16] Furlanetto, F. and N. Groshenny, “Mismatch shocks and unemployment during the Great Recession,” Working Paper 2013

[17] Gali, J., “Monetary Policy and Unemployment,” in B. Friedman and M. Woodford (eds.) Handbook of Monetary Economics, vol. 3A, 2011, 487-546

[18] Gali, J., “Note for a New Guide to Keynes (I): Wages, Aggregate Demand, and Employment,” Journal of the European Economic Association, vol. 11(5), 2013, 973-1003

[19] Gali, J., Smets, F. and R. Wouters, “Unemployment in an Estimated New Keynesian Model,” NBER Macroeconomics Annual 2011, University of Chicago Press, 329-360

[20] Gertler, M., Gali, J. and J. David Lopez-Salido, “Markups, Gaps, and the Welfare Costs of Business Fluctuations,” Review of Economics and Statistics, 89(1), 2007, 44-59

[21] Gertler, M., Sala, L. and A. Trigari, “An Estimated Monetary DSGE Model with Unemployment and Staggered Nominal Wage Bargaining,” Journal of Money, Credit and Banking, 2008, 40(8), 1713-1764

[22] Hall, Robert E., “Macroeconomic Fluctuations and the Allocation of Time,” Journal of Labor Economics, 15(1),1997, 223-250

[23] Hornstein, A., “The Cyclicality of the Labor Force Participation Rate,” Working Paper May 2013

[24] Justiniano, A., Primiceri, G., and A. Tambalotti, “Is There a Trade-Off between Inflation and Output Stabilization,” American Economic Journal: Macroeconomics, vol. (2), 2013, 1-31

[25] Pappa, E., “The Effect of Fiscal Shocks on Employment and the Real Wage,” International Economic Review, 50 (2009), 217-244

[26] Peersman, G., and R. Straub, “Technology Shocks and Robust Sign Restrictions in a Euro Area SVAR,” International Economic Review, 50 (2009), 727-750

[27] Rubio-Ramirez, J.F., D.F. Waggoner and T. Zha, ”Structural Vector Autoregressions: Theory and Identification Algorithms for Inference,” Review of Economic Studies, vol. 77, 2010, 665-696

[28] Sala, L., Soderstrom; U. and A. Trigari, “Monetary Policy under Uncertainty in an Estimated Model with Labor Market Frictions,” Journal of Monetary Economics, 2008, 983-1006

[29] Sims, C., J. Stock, and M. Watson, ”Inference in Linear Time Series Models with Some Unit Roots,” Econometrica, vol. 58, 1990, 113-144

[30] Sims, C. and H. Uhlig, ”Understanding Unit Roots: A Helicopter Tour,” Econometrica, vol. 59, 1991, 1591-1599

[31] Uhlig, H., ”What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure,” Journal of Monetary Economics, vol. 52, 2005, 381-419

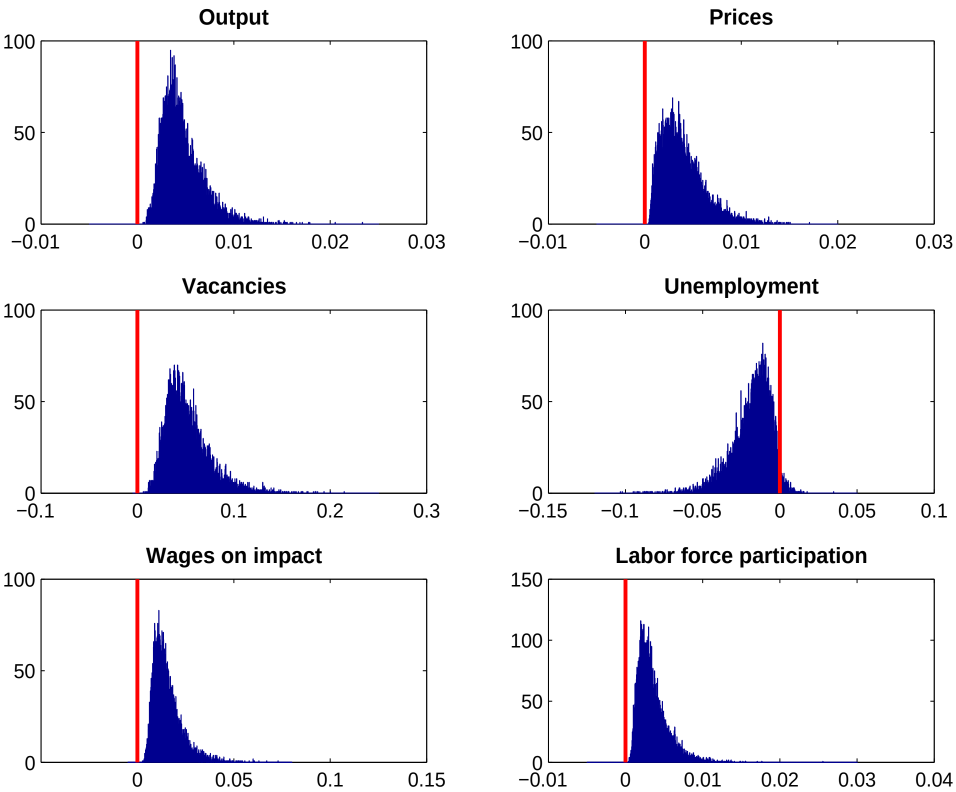


Figure 1: Distribution of impact responses to a 1% risk premium shock.

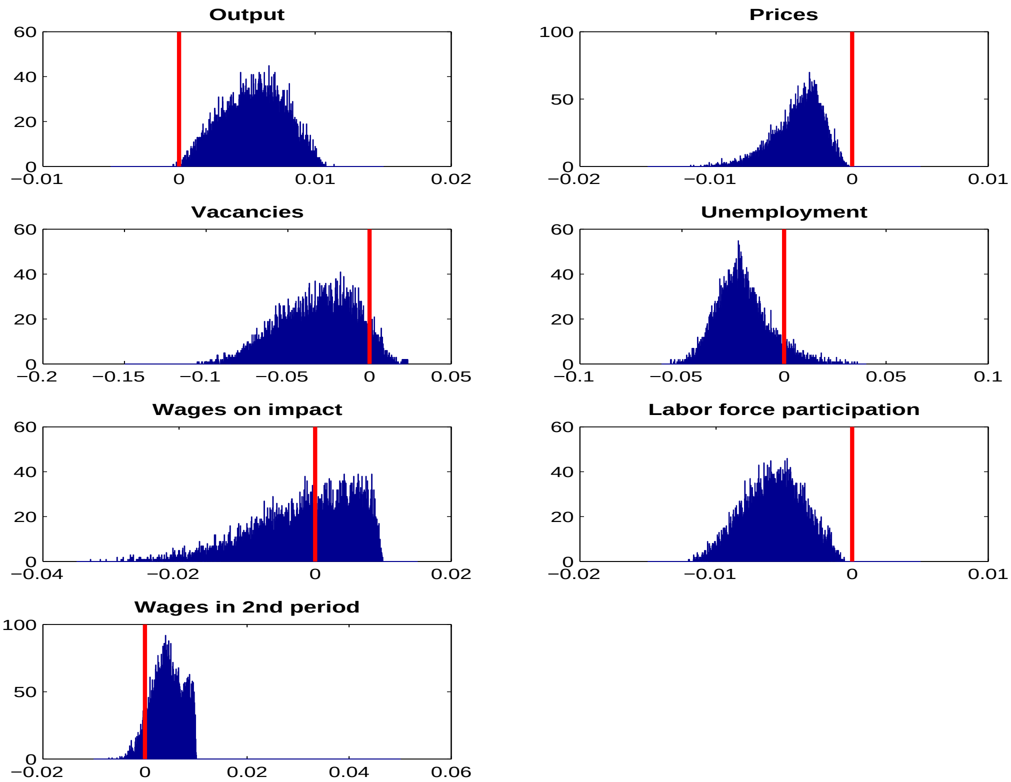


Figure 2: Distribution of impact responses to a 1% technology shock.

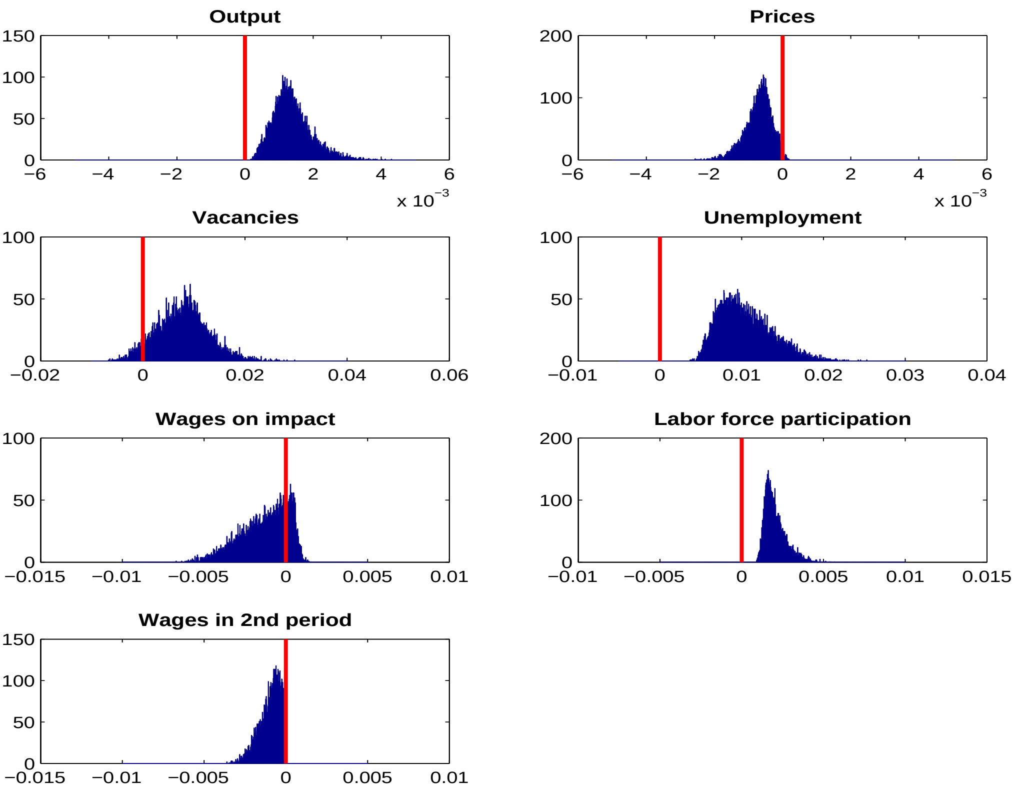


Figure 3: Distribution of impact responses to a 1% labor supply shock.

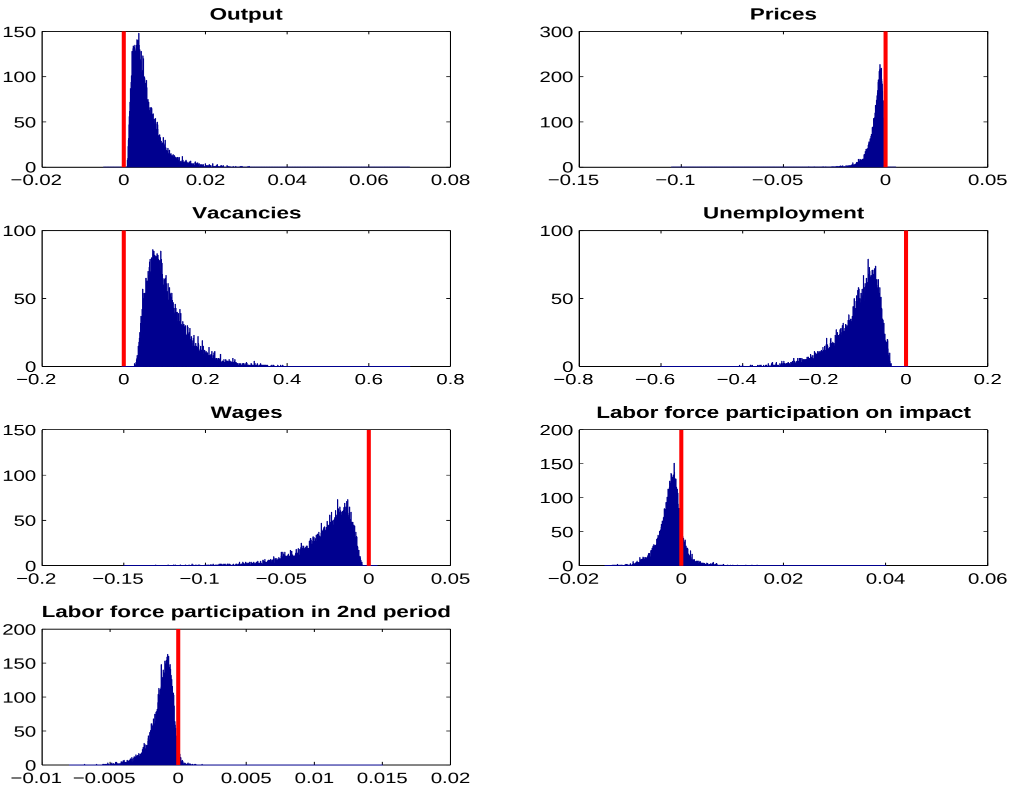


Figure 4: Distribution of impact responses to a 1% wage bargaining shock.

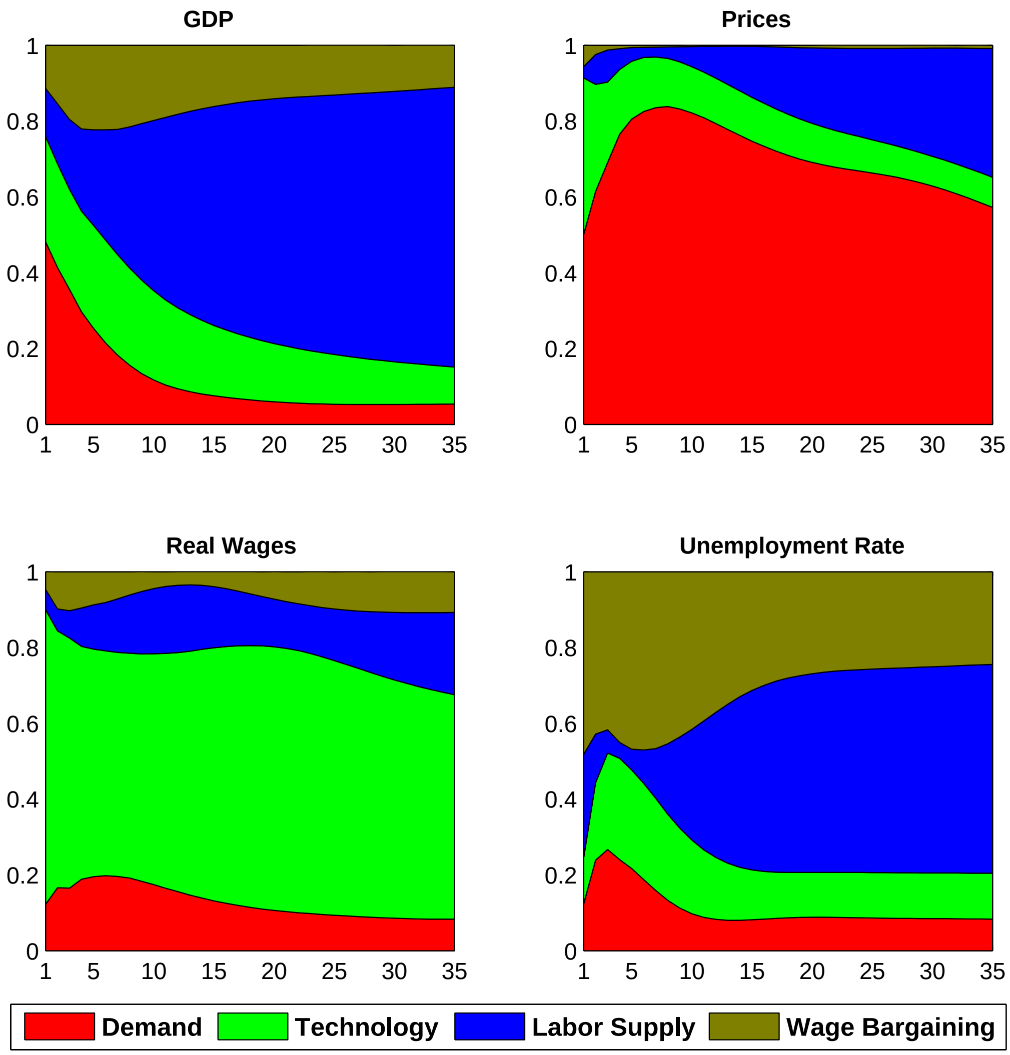


Figure 5: Variance decomposition for the baseline VAR model

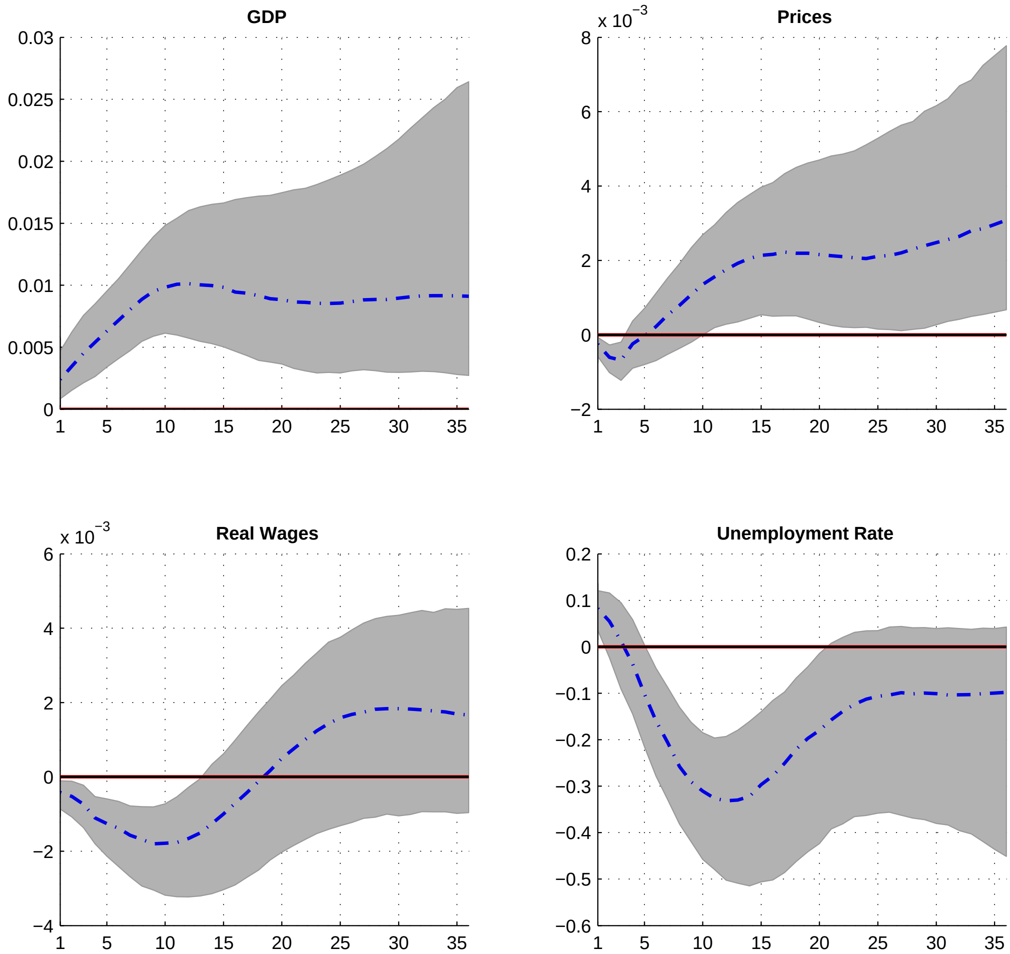


Figure 6: Impulse responses to a labor supply shock in the baseline VAR model.

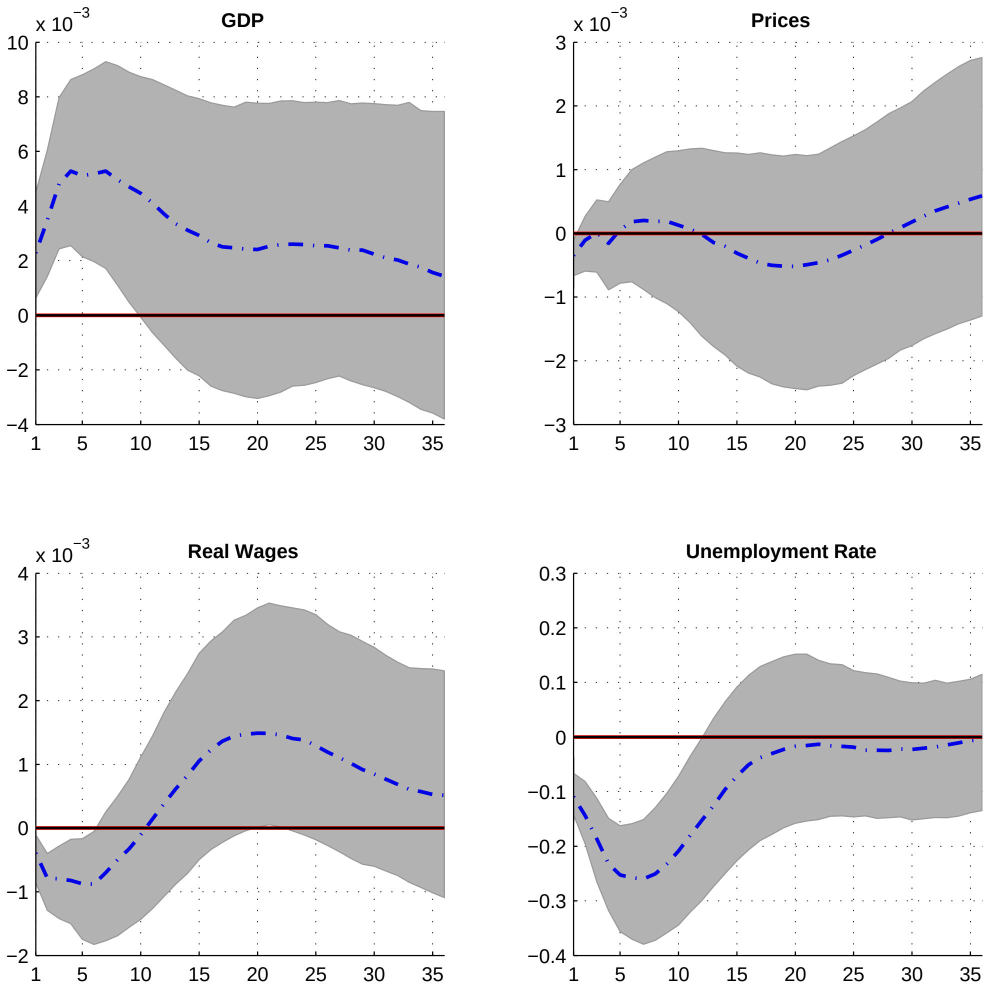


Figure 7: Impulse responses to a wage bargaining shock in the baseline VAR model

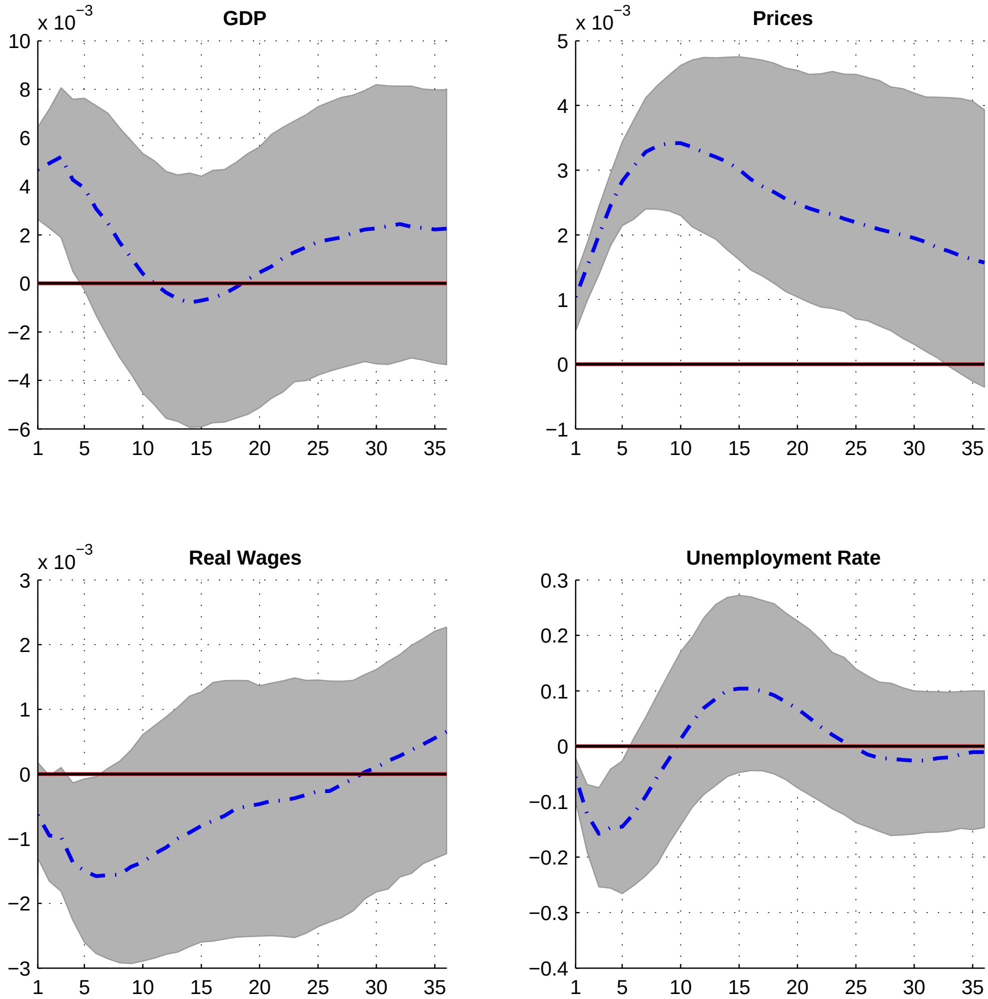


Figure 8: Impulse responses to a demand shock in the baseline VAR model.

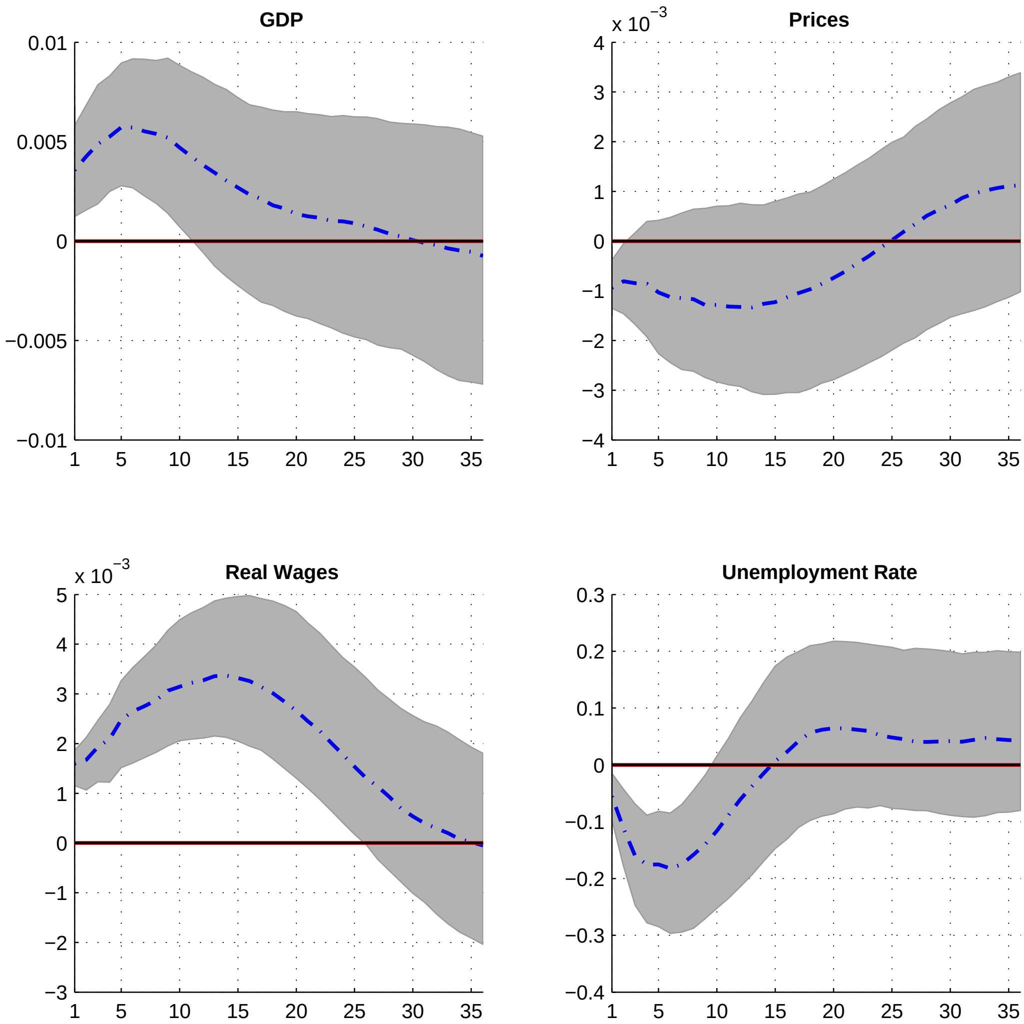


Figure 9: Impulse responses to a technology shock in the baseline VAR model.

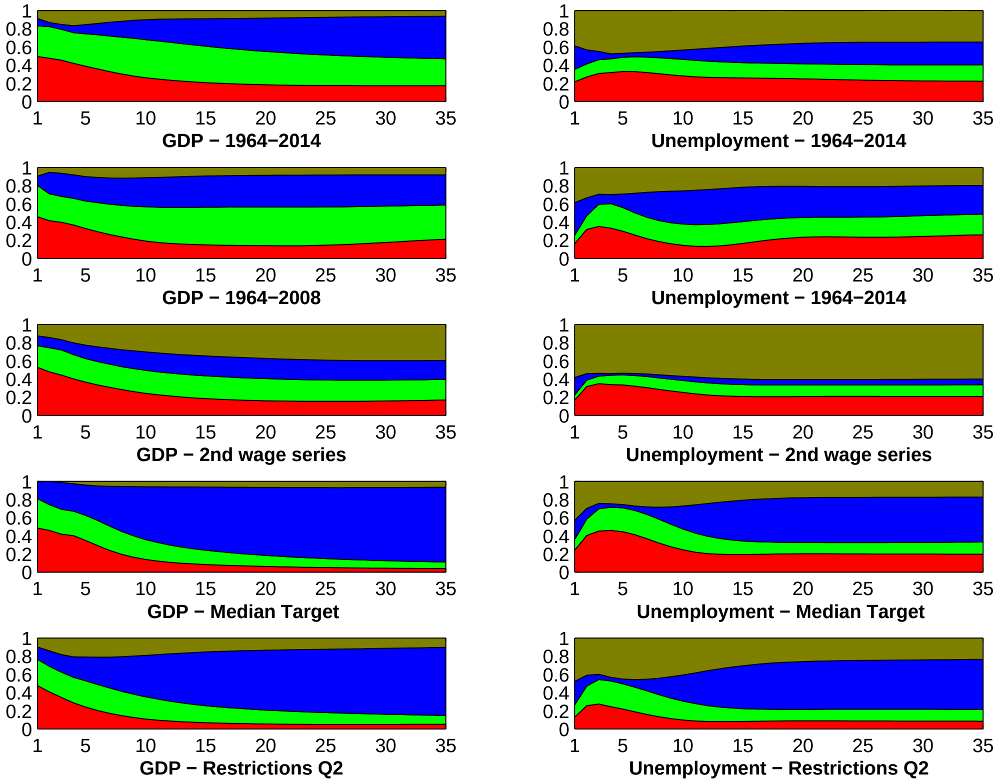


Figure 10: Sensistivity analysis for the baseline VAR model.

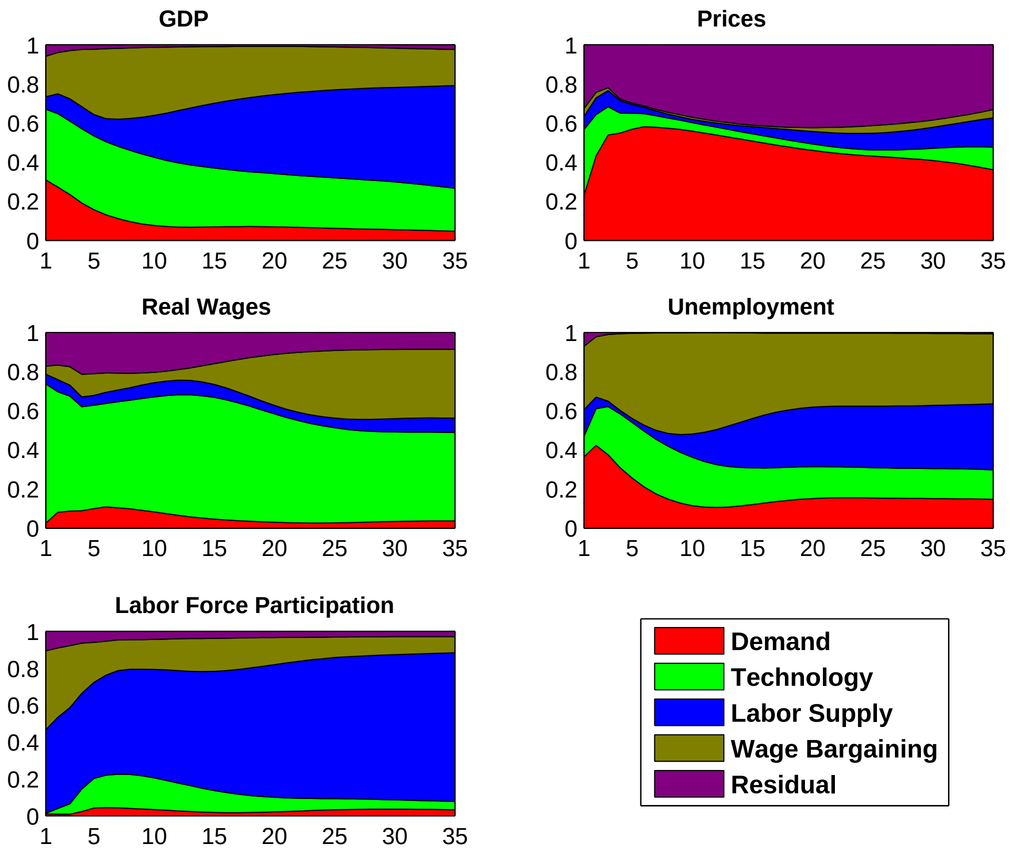


Figure 11: Variance decomposition for the extended VAR model with data on labor force participation.

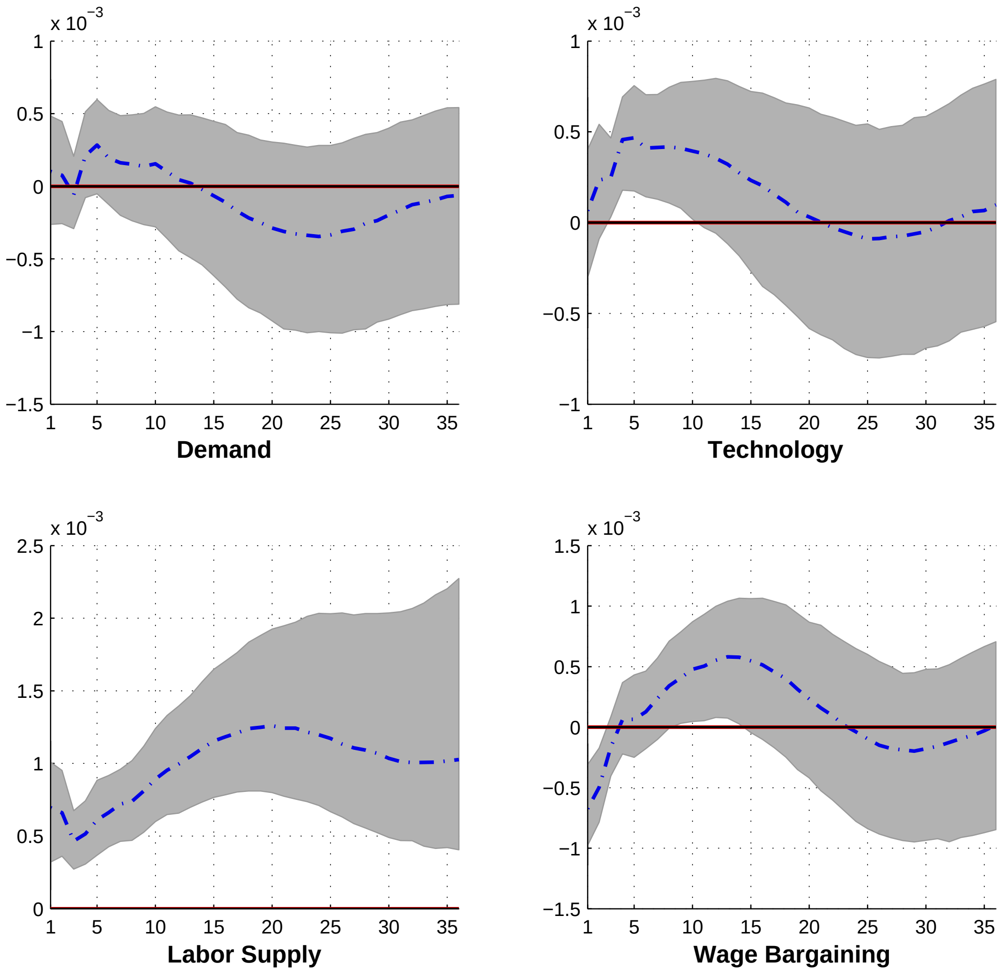


Figure 12: Impulse responses of the participation rate to the four identified shocks.

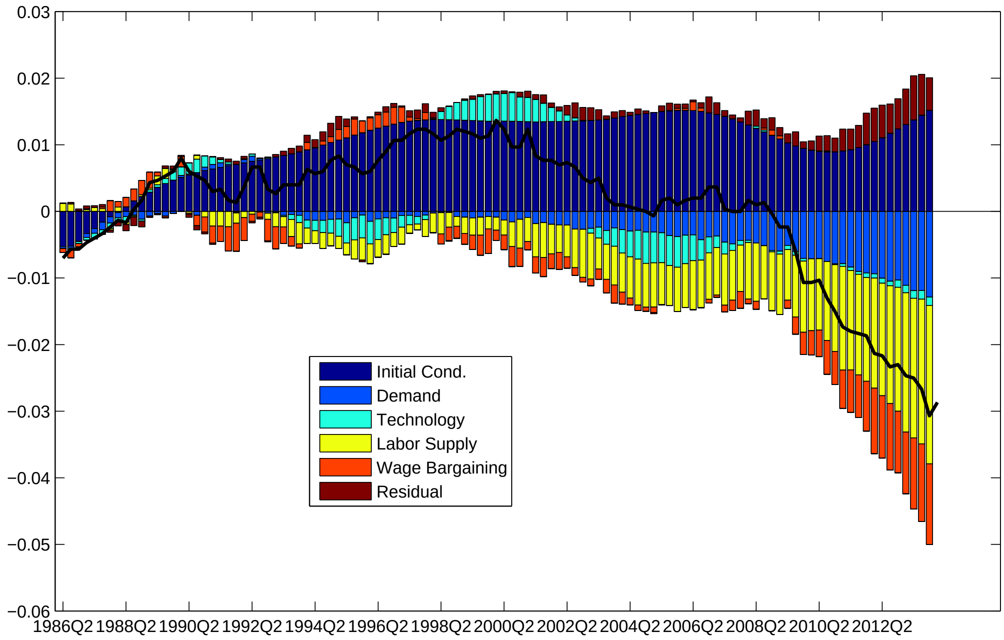


Figure 13: Historical decomposition for the labor force participation rate in deviation from its mean (solid line).

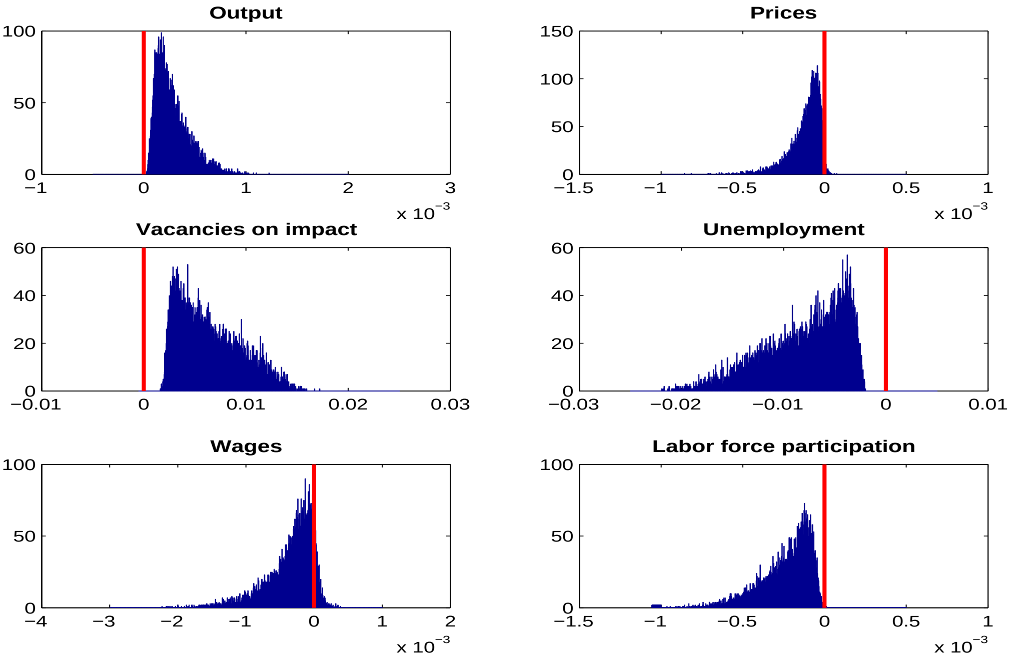


Figure 14: Distribution of impact responses to a 1% unemployment benefit shock.

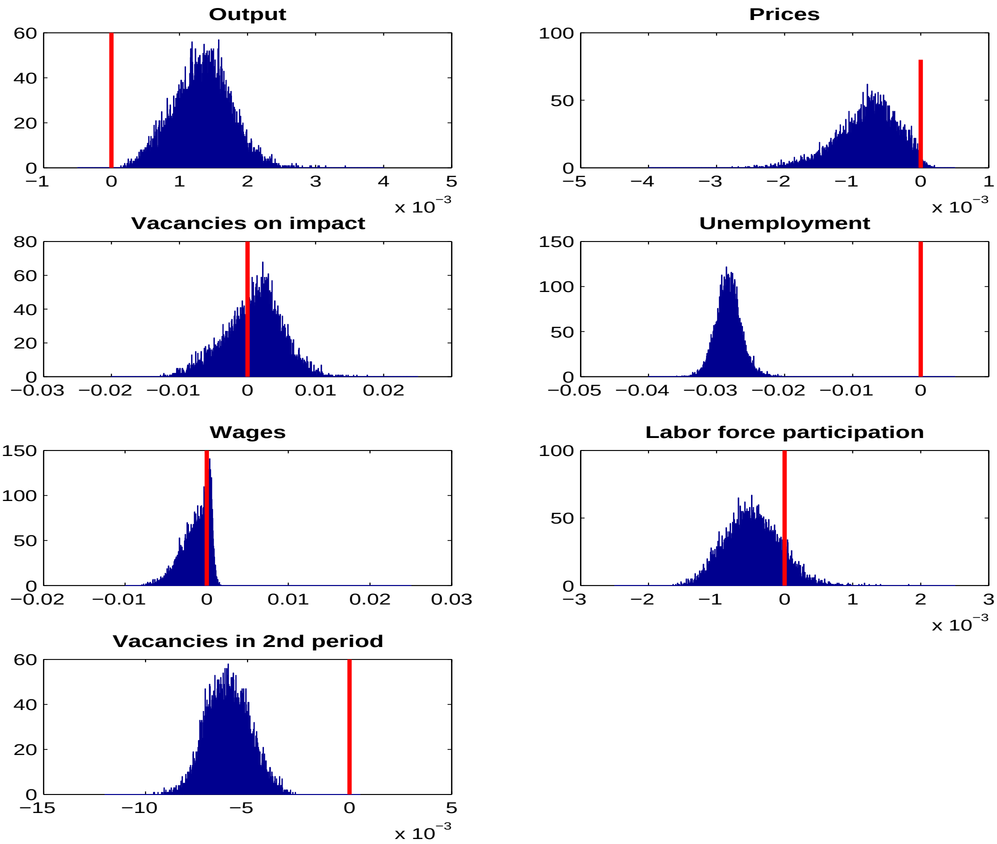


Figure 15: Distribution of impact responses to a 1% matching efficiency shock.

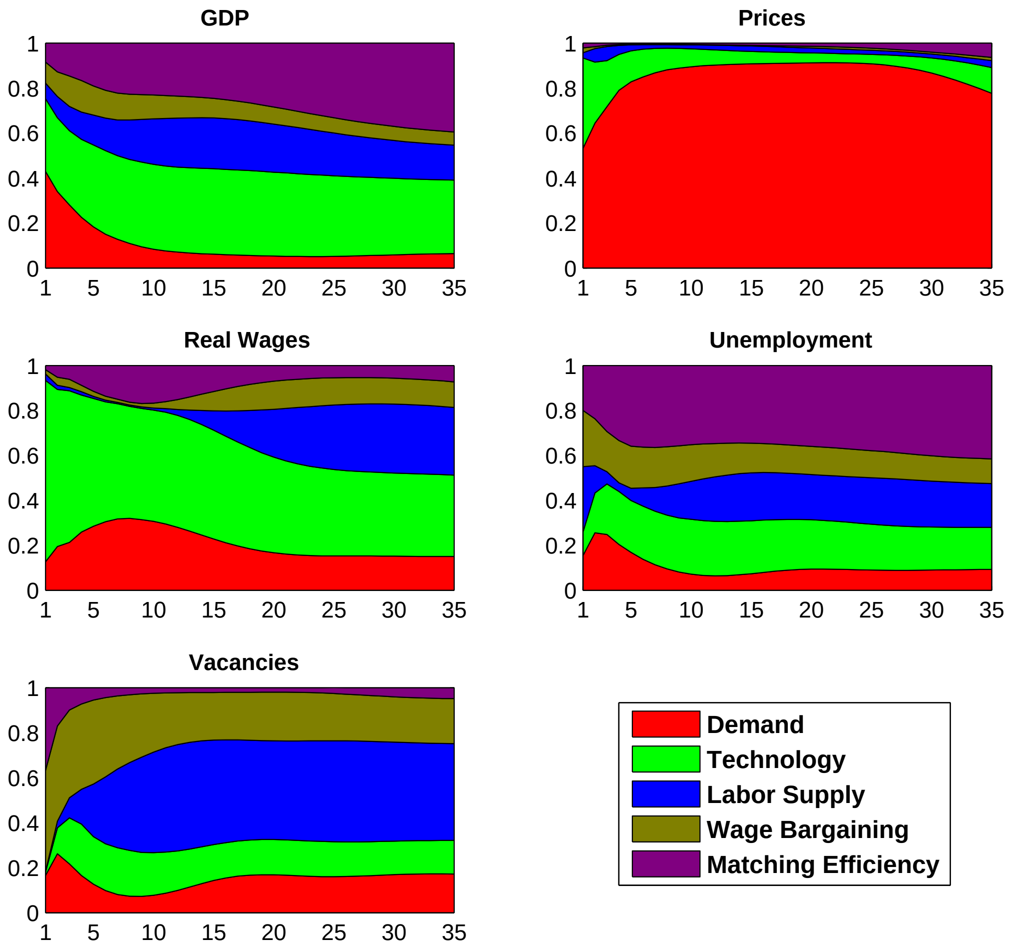


Figure 16: Variance decomposition in VAR model extended with data on vacancies.

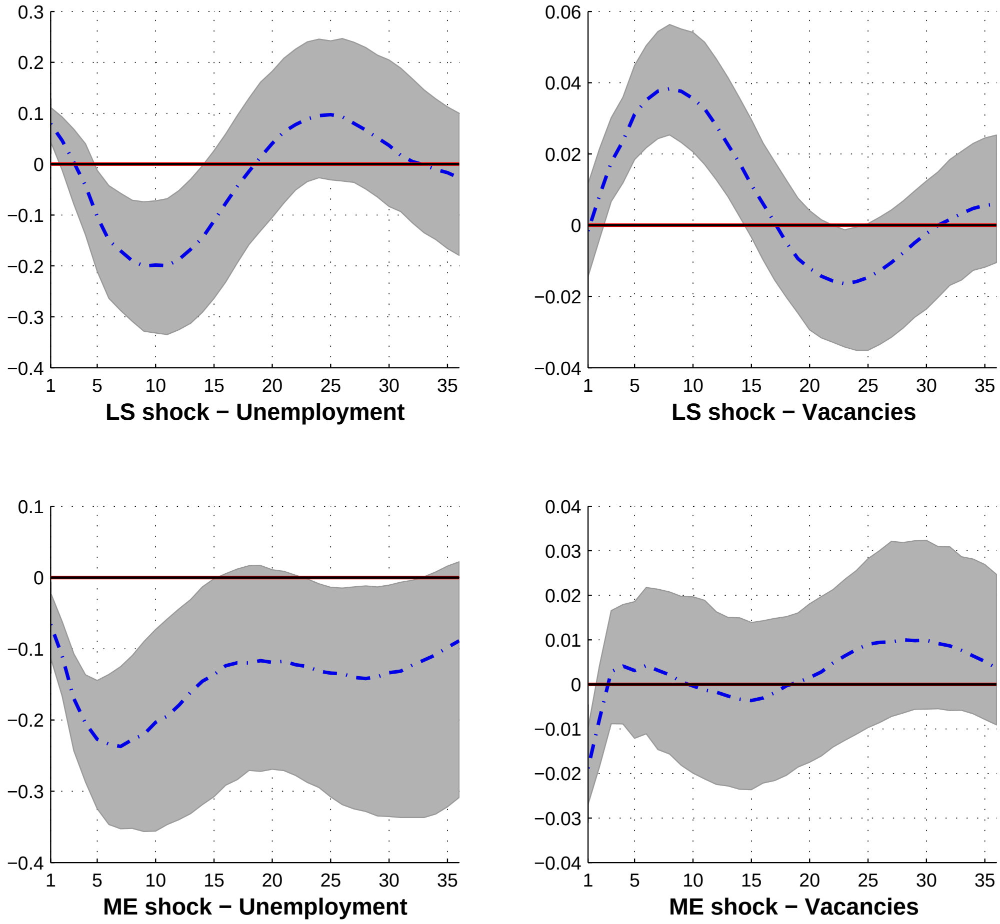
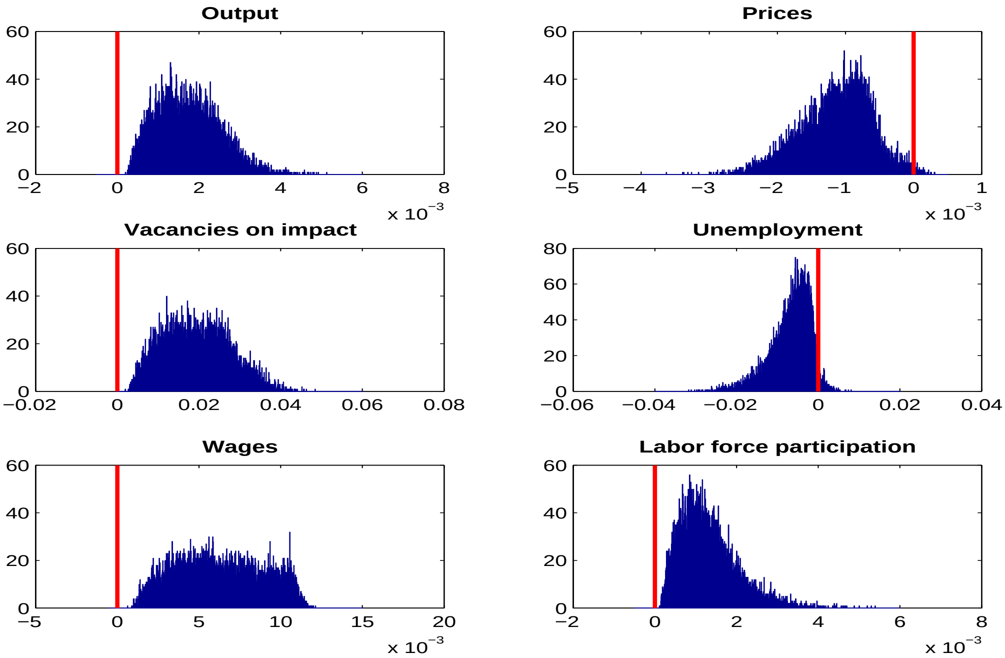


Figure 17: Impulse responses of unemployment and vacancies to labor supply and matching efficiency shocks


Output
x 10^−3
Prices
x 10^−3
Vacancies on impact
Unemployment
Wages
x 10^−3
Labor force participation
x 10^−3

A Appendix

A.1 Log-linear equations characterizing the decentralized equilibrium

- $c_t = c_{t+1} - \frac{1}{\sigma}(i_t - E_t\pi_{t+1} + \varepsilon_t^p)$
- $\frac{\kappa}{\Gamma}\theta^\alpha(\alpha\theta_t - \gamma_t) = \frac{Z}{\mu}(z_t - \mu_t) - ww_t + \beta(1-\rho)\frac{\kappa}{\Gamma}\theta^\alpha(\sigma c_t - \sigma E_t c_{t+1} + \alpha E_t\theta_{t+1} - E_t\gamma_{t+1})$
- $ww_t = bb_t + \frac{\eta}{1-\eta}\frac{\kappa}{\Gamma}\theta^\alpha\left[\frac{\varepsilon_t^\eta}{1-\eta} - \gamma_t + \alpha\theta_t\right] - \beta(1-\rho)\frac{\eta}{1-\eta}\frac{\kappa}{\Gamma}\theta^\alpha(1-p)\left(\sigma c_t - \sigma E_t c_{t+1} + \frac{\varepsilon_{t+1}^\eta}{1-\eta} - \gamma_{t+1} + \alpha\theta_{t+1}\right)$
- (continued): $\beta(1-\rho)\frac{\eta}{1-\eta}\frac{\kappa}{\Gamma}\theta^\alpha pp_{t+1}$
- $\pi_t = \beta E_t\pi_{t+1} - \frac{(1-\beta\delta)(1-\delta)}{\delta}\mu_t$
- $\chi L^\varphi C^\sigma(\varphi l_t + \sigma c_t + \chi_t) = p(w-b)p_t + (1-p)bb_t + pww_t + \beta(1-\rho)(1-p)(\chi L^\varphi C^\sigma - b)(p_t + \sigma c_t)$
- (continued): $+\beta(1-\rho)\chi L^\varphi C^\sigma(1-p)(\chi_{t+1} + \varphi l_{t+1}) - \beta(1-\rho)(\chi L^\varphi C^\sigma - b)p_{t+1} + \beta(1-\rho)(1-p)b(\sigma c_{t+1} - b_{t+1})$
- $cc_t + \kappa\theta(L - (1-\rho)N)\theta_t + \kappa\theta L l_t - \kappa(1-\rho)N\theta n_{t-1} = ZN(z_t + n_t)$
- $n_t = (1-\rho)(1-p)n_{t-1} + \frac{pL}{N}l_t + p(\frac{L}{N} - 1 + \rho)p_t$
- $i_t = \phi_r i_{t-1} + (1-\phi_r)(\phi_\pi\pi_t + \phi_y y_t)$
- $p_t = (1-\alpha)\theta_t + \gamma_t$
- $\eta_t = \varepsilon_t^\eta$
- $z_t = \zeta^Z z_{t-1} + \epsilon_t^Z$
- $\varepsilon_t^p = \zeta^p\varepsilon_{t-1}^p + \epsilon_t^p$
- $\varepsilon_t^\eta = \zeta^\eta\varepsilon_{t-1}^\eta + \epsilon_t^\eta$
- $\gamma_t = \zeta^\Gamma\gamma_{t-1} + \epsilon_t^\Gamma$
- $b_t = \zeta^b b_{t-1} + \epsilon_t^b$
- $\chi_t = \zeta^\chi\chi_{t-1} + \epsilon_t^\chi$

A.2 Data sources

This subsection lists the sources of the data series used in the estimation of the VAR

- **Unemployment rate**: taken from the website of the Bureau of Labor Statistics "Labor Force Statistics from the Current Population Survey", series ID LNS14000000, seasonally adjusted, 16 years over
- **Civilian labor force particpation rate**: taken from the website of the Bureau of Labor Statistics, series ID LNS11300000, seasonally adjusted, 16 years over

- **Vacancies**: We use the Help Wanted Index of the Conference Board from 1951m1 to 1994m12 and Barnichon's (2010) index from 1995m1 to 2013m6. We also have JOLTS data for job openings from 2000m12 to 2014m3. In order to construct a series for vacancy levels, we apply the following formula $V_t = \frac{HWI_t * \bar{V}_{2000m12-2013m6}}{H\bar{W}I_{2000m12-2013m6}}$ where $\bar{V}_{2000m12-2013m6}$ is the average of job openings in JOLTS and $H\bar{W}I_{2000m12-2013m6}$ is the average of the help wanted index over the period 2000m12 to 2013m6. For the period 2013m6 to 2014m3, we use directly JOLTS data.
- **Prices**: taken from the FRED. Gross Domestic Product: Implicit Price Deflator, Index 2009=100, Quarterly, Seasonally Adjusted, GDPDEF
- **Output**: Quarterly real output in the non farm sector constructed by the BLS MSPC program, ID SERIES PRS85006043, base year 2009.
- **Nominal wages 1**: taken from the website of the Bureau of Labor Statistics. Average Hourly Earnings of Production and Nonsupervisory Employees, ID series CES0500000008, seasonally adjusted. Available only from 1964 onwards.
- **Nominal wages 2**: taken from the Fred. Nonfarm Business Sector: Compensation Per Hour, Index 2009=100, Quarterly, Seasonally Adjusted, COMPNFB.

When the original data is at a monthly frequency, we take quarterly averages of monthly data. Nominal wages are deflated using the implicit price deflator of GDP to obtain real wages.

A.3 Bayesian Estimation of the VAR

We illustrate in this Appendix the econometric procedure we use for the estimation of the different VAR models we present in the paper.

We start from the standard reduced-form VAR representation:

$$y_t = C_B + \sum_{i=1}^{P} B_i y_{t-i} + u_t, \tag{16}$$

where y_t is a $N \times 1$ vector containing our N endogenous variables, C_B is a $N \times 1$ vector of constants, B_i for $i = 1, ..., P$ are $N \times N$ parameter matrices, with P the maximum number of lags we include in the model (5 in our specific case), and u_t is the $N \times 1$ one-step ahead prediction error with $u_t \sim N(0, \Sigma)$, where Σ is the $N \times N$ variance-covariance matrix.

Due to the substantial large number of parameters to be estimate, we prefer to estimate our models using Bayesian methods. Moreover, the models are specified and estimated with variables in levels. This is a nice feature of the Bayesian approach, which can be applied regardless of the presence of nonstationarity (see Sims, Stock, and Watson (1990) and Sims and Uhlig (1991) for more deails on this point).

Estimation procedure

The VAR model described in equation 16 can be rewritten in a compact way as:

$$\mathbf{Y} = \mathbf{XB} + \mathbf{U}, \tag{17}$$

where $\mathbf{Y} = [y_1 \; \dots \; y_T]'$, $\mathbf{B} = [C_B \; B_1 \; \dots \; B_p]'$, $\mathbf{U} = [u_1 ... u_T]'$, and

$$\mathbf{X} = \begin{bmatrix} 1 & y_0' & \dots & y_{-p}' \\ \vdots & \vdots & \vdots & \vdots \\ 1 & y_{T-1}' & \dots & y_{T-p}' \end{bmatrix}.$$

Finally, for convenience, we rewrite17 into its vectorized form:

$$\mathbf{y} = (I_n \otimes \mathbf{X})\beta + \mathbf{u}, \tag{18}$$

where $\mathbf{y} = vec(\mathbf{Y})$, $\beta = vec(\mathbf{B})$, $\mathbf{u} = vec(\mathbf{U})$, and with $vec()$ denoting columnwise vectorization. The error term $\mathbf{u}$ follows a normal distribution with a zero mean and variance-covariance matrix $\Sigma \otimes I_T$.

The likelihood function in $\mathbf{B}$ and Σ is defined as:

$$L(B, \Sigma) \propto |\Sigma|^{-\frac{T}{2}} \exp\left\{-\frac{1}{2}(\beta - \hat{\beta})'^{-1} \otimes \mathbf{X}'\mathbf{X})(\beta - \hat{\beta})\right\} \exp\left\{-\frac{1}{2}tr(\Sigma^{-1}S)\right\},$$

where $S = ((\mathbf{Y} - \mathbf{X}\hat{\mathbf{B}})'(\mathbf{Y} - \mathbf{X}\hat{\mathbf{B}}))$ and $\hat{\beta} = vec(\hat{\mathbf{B}})$ with $\hat{\mathbf{B}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$. We specify diffuse priors so that the information in the likelihood is dominant and these priors lead to a Normal-Wishart posterior. More in detail, we a diffuse prior for β and Σ that is proportional to $|\Sigma|^{-(n+1)/2}$. The posterior becomes:

$$p(B, \Sigma|y) \propto |\Sigma|^{-\frac{T+n+1}{2}} \exp\left\{-\frac{1}{2}(\beta - \hat{\beta})'^{-1} \otimes \mathbf{X}'\mathbf{X}](\beta - \hat{\beta})\right\} \exp\left\{-\frac{1}{2}tr(\Sigma^{-1}S)\right\}, \tag{19}$$

where y denotes all available data.

The posterior in equation 19 is the product of a normal distribution for β conditional on Σ and an inverted Wishart distribution for Σ (see, e.g. Kadiyala and Karlsson, 1997 for the proof). We then draw β conditional on Σ from

$$\beta|\Sigma, y \sim N(\hat{\beta}, \Sigma \otimes (\mathbf{X}'\mathbf{X})^{-1})$$

and Σ from

$$\Sigma|y \sim IW(S, \nu),$$

where $\nu = (T - n) * (p - 1)$ and N representing the normal distribution and IW the inverted Wishart distribution.

Identification procedure

In order to map the economically meaningful structural shocks from the reduced form estimated shocks, we need to impose restrictions on the variance covariance matrix we estimated.

In detail, the prediction error u_t can be written as a linear combination of structural innovations ϵ_t

$$u_t = A\epsilon_t$$

with $\epsilon_t \sim N(0, I_N)$, where I_N is an $(N \times N)$ identity matrix and where A is a non-singular parameter matrix. The variance-covariance matrix has thus the following structure $\Sigma = AA'$.

Our goal is to identify A from the symmetric matrix Σ, and to do that we need to impose restrictions.

In this paper we choose a now popular approach in the literature based on sign restrictions (see Canova and De Nicolo', 2002, Uhlig, 2005, and Fry and Pagan, 2011 among others on this identification method). Alternative methods are proposed in the literature to deal with identification issues. In particular, the most famous approach is the Cholesky identification, which implies a recursive identification scheme. Other famous approaches are long-run restrictions or identification through heteroskedasticity. However, none of these approaches seem suited for the purpose of our analysis.

To obtain identification via sign restrictions, we follow the procedure described in Rubio-Ramirez, Waggoner and Zha (2010). The algorithm has the following steps. First, we compute A as the Cholesky decomposition of our estimated variance covariance matrix. We then compute rotations of this matrix, computing first a matrix Q with a QR decomposition of $X = QR$, where X is drawn from $X \sim N(0, I_N)$. Then, we generate candidate impulse responses from AQ and B_i for $i = 1, ..., P$ and check if the generated impulse responses satisfy the sign restrictions. If the sign restrictions are satisfied, we store our impulse response, if not we draw a new X. We iterate over the same procedure again until we obtain 1000 impulse responses which satisfy our sign restrictions.

A.4 Introducing price-markup shocks

This subsection provides an extension to the analysis carried out in section 5. The residual shock is replaced by a shock with an economic interpretation, a price-markup shock. This shock is introduced in the theoretical framework by assuming that the elasticity of substitution between goods ε is stochastic. In the model, the market power of firms comes from the imperfect substituability between goods. Thus, an increase in ε leads to a decrease in firms' markups. The distribution of impact responses to a price-markup shock is presented in Figure 18. An increase in the elasticity of substitution between goods leads to a decrease in prices and an increase in aggregate demand. In order to produce more, firms recruit more workers and unemployment decreases. The decrease in unemployment puts upward pressure on wages. The increase in the job-finding rate and in wages tend to make labor force participation relatively more interesting whereas the increase in consumption tends to make labor force participation relatively less interesting. The first effect dominates under all parameterizations. Notice that the price-markup shock implies the same dynamics for output, prices and wages than the technology shock. However, the behavior of participation is markedly different in response to the two shocks. Participation decreases following a technology shock whereas it increases following a price-markup shock. We use this asymmetric response of participation in order to identify the two shocks in the VAR.

Figure ? presents the variance decomposition for the extended model with price-markup shocks. Our main result, namely that labor supply shocks and wage bargaining shocks are important drivers of output and unemployment fluctuations, is confirmed. The price-markup shock accounts for a small but significant share of unemployment and labor force participation fluctuations in the short-run. It also accounts for a large share of movements in the real wage at all frequencies.