Labor Supply Factors and Economic Fluctuations*

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First Version: June 2014
This Version: June 2016

Abstract

We propose a new VAR identification scheme that enables us to disentangle labor supply shocks from wage bargaining shocks. Identification is achieved by imposing robust sign-restrictions that are derived from a New Keynesian model with endogenous labor force participation. 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

J.E.L. Codes: C11, C32, E32.

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*This working paper should not be reported as representing the views of Norges Bank and Banque de France. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank and Banque de France. For their useful comments, we thank Florin Bilbiie, Jeff Campbell, Ambrogio Cesa Bianchi, Efrem Castelnuovo, Marco Del Negro, Martin Eichenbaum, John Fernald, Giuseppe Fiori, Jordi Galí, Nicolas Groshenny, Jean-Olivier Hairault, Alejandro Justiniano, Michele Lenza, Pietro Peretto, Aysegul Sahin, Jim Stock, Andrea Tambalotti, Carl Walsh, Sebastian Weber and seminar participants at BI Norwegian Business School, Federal Reserve Bank of New York, Federal Reserve Bank of San Francisco, HEC Montreal, North Carolina State-Duke joint seminar, Paris School of Economics, Reserve Bank of Australia, Reserve Bank of New Zealand, University of Adelaide, University of California Santa Cruz, University of Glasgow, University of Melbourne and University of Texas Austin.

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1 Introduction

A well-known, and often criticized, feature of modern macroeconomic models is that they rely on large labor market shocks to explain business cycle dynamics (cf. Smets and Wouters, 2003 and 2007, Chari, Kehoe and McGrattan, 2009, Justiniano, Primiceri and Tambalotti, 2013, among others). In practice these labor market shocks have been modeled either as exogenous shifts in the disutility of supplying labor or as movements in wage mark-ups. Unfortunately, quantifying the relative importance of these two labor market shocks has proven to be challenging because they generate dynamics that are observationally equivalent. The objective of this paper is to separately identify the two disturbances, namely labor supply and wage bargaining shocks,[1] and quantify their importance for economic fluctuations in the context of a Vector Auto Regressive (VAR) model. To achieve our goals, we propose a new identification scheme based on sign-restrictions that enables us to disentangle the two shocks.[2]

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 for identification purposes in the VAR. Labor supply shocks and wage-markup shocks have been shown to be observationally equivalent in the standard New Keynesian model. In our theoretical framework, the presence of search frictions in the labor market and of the labor force

[1]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.

[2]The use of sign restrictions in VAR models has been pioneered by Canova and De Nicolo' (2002), Faust (1998), Peersman (2005) and Uhlig (2005). We follow Canova and Paustian (2011), Mumtaz and Zanetti (2012), 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).

participation margin 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 in the long run since they account for more than 60% of fluctuations in output and 50% in unemployment at a 30-quarter horizon. Wage bargaining shocks are more important at short horizons but also play a non-negligible role in the long run, especially for unemployment. While the two shocks are of comparable importance across alternative specifications, their joint importance is magnified by the presence of the Great Recession in our sample period. Nevertheless, even when we extend or reduce the sample period, the role of labor market shocks remains substantial.

Our 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 and labor supply shocks and that labor supply is not influenced by aggregate demand and the level of technology. They find that labor supply shocks are the most important driver of output and hours at low frequencies. 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. Blanchard and Diamond, 1989, and Chang and Schorfheide, 2003, on US data and Peersman and Straub, 2009, on euro area data) in VAR models identified with impact or sign restrictions. We contribute to this literature by refining the identification of labor supply shocks since earlier VAR studies do not disentangle labor supply shocks from wage bargaining shocks. Nevertheless, as in the previous literature, we find that labor supply shocks play an important role at all horizons.

Our findings are also related to the Dynamic Stochastic General Equilibrium (DSGE) literature dealing with shocks originating in the labor market. Smets and Wouters (2003) and Chari, Kehoe and McGrattan (2009) observe that in a New Keynesian model these labor market shocks could either be interpreted as an efficient shock to preferences or as an inefficient wage mark-up 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. Galí, Smets and Wouters (2011) propose a reinterpretation of the standard New Keynesian model in which unemployment emerges because of the monopoly power of unions. This set-up allows them to disentangle labor supply shocks from wage-markup shocks. However, their modeling assumption implies that long-run movements in unemployment are restricted 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 demand shocks and wage bargaining shocks. Analysis of the recent decline in the participation rate in the US include Bullard (2014), Erceg and Levin (2014), Fujita (2014), Hornstein (2013) and Kudlyak (2013), among others. Barnichon and Figura (2015) use micro data on labor market flows to analyze the role of demographic and other labor supply factors in explaining the downward trends in participation and in unemployment. Elsby, Hobijn 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), Brückner and Pappa (2012), Campolmi and Gnocchi (2016), Christiano, Eichenbaum and Trabandt

(2015) and Galí, Smets and Wouters (2011), among others, model the participation decision in the context of DSGE models. Christiano, Trabandt and Walentin (2012) and Galí (2011) study the response of the participation rate to monetary, technology and investment-specific shocks in VAR models identified with short-run and long-run restrictions. Unlike previous contributions, we provide evidence on the response of participation to different shocks using an identification scheme based on sign restrictions. In addition, to the best of our knowledge, we are the first to provide a VAR perspective on the recent dynamics.

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 to identify structural shocks in a VAR model estimated with Bayesian methods. Section 4 presents the results. Section 5 discusses the participation rate dynamics, while 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 that departs from the standard New Keynesian model in two ways. First, the labor market is not perfectly competitive but is characterized by search and matching frictions. Second, the labor force participation decision is modeled explicitly. 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). Our contribution is not in the development of the model, which largely builds on Arseneau and Chugh (2012) and Galí (2011), but in showing that this set-up can break the observational equivalence between labor supply and wage bargaining shocks. The two labor market shocks, as well as all the other shocks in the model, follow an autoregressive process of order one.

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 that evolves exogenously. $\alpha \in [0, 1]$ 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 of filling a vacancy and the probability p_t for a worker of finding 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 (2015) 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], N the number of employed workers and L the size of the labor force. At the beginning of the following period, the representative household chooses the number of non-participants τ it transfers to the labor force. The size of the labor force in period t is thus given by $L_t = \omega(L_{t-1} - N_{t-1} - \rho N_{t-1}) + (1 - \rho)N_{t-1} + \tau_t$ and the number of job seekers by $s_t = \omega(L_{t-1} - (1 - \rho)N_{t-1}) + \tau_t = L_t - (1 - \rho)N_{t-1}$. Employment evolves according to the following law of motion

$$N_t = (1 - \rho)N_{t-1} + m_t \tag{1}$$

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 $u_t = \frac{L_t - N_t}{L_t}$.

[3]As in Christiano, Eichenbaum and Trabandt (2015), we introduce this staying rate to account for the fact that workers move in both directions between unemployment, employment and participation. However, the introduction of ω has no impact on the equilibrium conditions of the model. The household adjusts the number of non-participants that enter the labor force (τ_t) according to the value of ω in order to reach its desired value of L_t. We check that $\tau_t > -\omega(L_t - (1 - \rho)N_{t-1})$ holds in every period, that is, that the number of job seekers is always positive.

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. 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 that represents the labor supply shock. φ is a parameter determining the shape of the distribution of work disutilities across individuals. The intertemporal 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 participates in the labor force 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 risk sharing of consumption among household members implies $C_{it} = C_t$ for all i. The household's aggregate utility function is then given by

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

These preferences are akin to those used by Arseneau and Chugh (2012) and Galí (2011) when the disutility of participating in the labor force is identical for employed and unemployed workers.[4] The household chooses L_t and next period bond holdings B_{t+1} so as to maximize (2) subject to its budget constraint and its perceived law of motion of employment

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

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

[4] We also used an alternative specification in which unemployment individuals have a lower disutility of participating than employed individuals. Our identification assumptions are satisfied also in this extended set-up and results are available upon request. (FOOTNOTE NOT INTENDED FOR PUBLICATION).

Total labor income is given by $w_t N_t$ and unemployed household members receive unemployment benefits b_t, which evolve exogenously. 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 $(1+R_t)^{-1}$. They also have to pay lump-sum taxes T_t in order to finance the unemployment insurance system. The final consumption good $C_t \equiv \int_0^1 \left[C_t(z)^{\frac{\varepsilon_t - 1}{\varepsilon_t}} dz\right]^{\frac{\varepsilon_t}{\varepsilon_t - 1}}$ is a Dixit-Stiglitz aggregator of the different varieties of goods produced by the retail sector and ε_t is the elasticity of substitution between the different varieties. It follows an exogenous process and represents price mark-up shocks. The optimal allocation of income on each variety is given by $C_t(z) = \left[\frac{P_t(z)}{P_t}\right]^{-\varepsilon_t} C_t$, where $P_t = \left[\int_0^1 P_t(z)^{\varepsilon_t - 1} dj\right]^{1/(1-\varepsilon_t)}$ is the price index. ε_t^p is an exogenous premium in the return to bonds which follows an exogenous process. As explained in Fisher (2015), this term can be interpreted as a structural shock to the demand for safe and liquid assets such as short-term US Treasury securities.

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

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

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

where $\lambda_t = C_t^{-\sigma}$ is the marginal utility of consumption, $\beta_{t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-\sigma}$ is the stochastic discount factor of the household and $\Pi_{t+1} = \frac{P_{t+1}}{P_t}$ is price inflation in period $t+1$. 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 the event that job search is unsuccessful and the wage plus the continuation value of being employed if 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. Firms in the wholesale sector produce an intermediate homogeneous good in competitive markets using labor. Their output is sold to final good sector firms (retailers), which are monopolistically competitive and transform the homogeneous goods into differentiated goods at no extra cost and apply a mark-up. Firms in the retail sector are subject to nominal price staggering.

Wholesale firms. 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 at 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 the wage schedule as given. 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 mark-up 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 states that the cost of hiring a worker, i.e. the deadweight cost κ

multiplied 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 future savings on vacancy posting costs.

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 arising from the employment relationship 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 an exogenous process. We obtain the following sharing rule

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

After some algebra, we find

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

Note that 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. Thus, the introduction of search and matching frictions and of the participation margin in a New Keynesian model helps solve the observational equivalence problem between these two shocks.

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 the retailer's products is

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

where Y_t^d is aggregate demand for the final consumption good. Each retailer can reset its price with a fixed probability $1-\delta$ that is independent of the time elapsed since the last price adjustment. The Calvo pricing assumption implies that prices are fixed on average for $\frac{1}{1-\delta}$ periods. Retailers optimally choose 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 are then given by

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

2.4 Resource constraint and monetary policy

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

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

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

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

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

3 Robust sign restrictions

3.1 Methodology

We parameterize 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, while price mark-up shocks are considered in Appendix 4.

We use the theoretical model to derive sign restrictions that are robust to parameter uncertainty. In order to do so, we 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. While the interval for each parameter is independently and subjectively selected, one could make the ranges correlated and data-based using the approach of Del Negro and Schorfheide (2008). Here we follow Canova and Paustian (2009) who argue that the former approach is preferable since it provides information about the range of possible outcomes the model can produce, prior to the use of any data. We then draw a random value for each parameter, obtain a full set of parameters, 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 follow a stricter criterion by reporting the entire distribution in order to ensure the robustness of our sign restrictions. We focus on impact responses since only assumptions on the impact responses are used for identification in the VAR. Only in a few cases where the impact response is uncertain, we impose restrictions on the responses in the second period.

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 while the steady state job finding rate is fixed at 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 (cf. 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 (cf. Galí, Smets and Wouters, 2011, Gertler, Sala and Trigari, 2008, and Furlanetto and Groshenny, 2016). 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 mark-up 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 (2001). 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 mentioned above. Table 1 gives the ranges for all the parameters.

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

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 percentage 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]

response of output and prices. As the premium on safe assets decreases, it is of less interest 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 higher demand by producing more. As a consequence, 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. Notice that our identified demand shock should not be interpreted only as a risk premium shock. In fact, the restrictions that we impose are consistent also with other demand disturbances, such as monetary policy, government spending and discount factor 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. 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 may 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 (cf. Galí, 1999). Importantly, in the event of a strong drop in vacancies and of a rise in unemployment, the decrease in hiring costs may lead to a decrease in real wages on impact. However, real wages overshoot their steady-state value under almost all parameter configurations from period two onwards. We use the positive response of output and real wages and the negative response of prices to identify technology shocks.[5]

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. 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, thus contributing to lower marginal costs and prices. Since 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 clearly decreases. We use the positive response of output and the negative responses of wages, prices and unemployment to identify wage bargaining shocks. Table 2 provides a summary of the sign restrictions.

Table 2: Sign restrictions

	Demand	Technology	Labor Supply	Wage Bargaining
GDP	+	+	+	+
Prices	+	-	-	-
Real wages	/	+	-	-
Unemployment	-	/	+	-

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

It is the restriction on unemployment that enables us to separately identify the labor supply shock and the wage bargaining shock. Nonetheless, the participation response (procyclical to labor supply and countercyclical to wage bargaining) can help refine the identification.[6] We will explore this avenue in an extension in Section 5. We view our approach as being "agnostic" as we only need to use a minimal set of robust and arguably uncontroversial restrictions to identify the different structural shocks. Our results can then be used to evaluate the potential sources of mispecifications in DSGE models.

Importantly, our restrictions are not only robust to parameter uncertainty but also, to some extent, to model uncertainty. Shocks to the labor force increase unemployment also in the seminal paper by Blanchard and Diamond (1989). Furthermore, all the restrictions we impose are also satisfied in the estimated model by Galí, Smets and Wouters (2011) in which unemployment arises from the monopoly power of unions and preferences feature a very low wealth effect.

Our VAR identification scheme is also related 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 identify labor supply shocks separately 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.

4 Empirical results

In this section, we present the results derived from our baseline model that is estimated with Bayesian methods on quarterly data in levels from 1985Q1 to 2014Q1 for the US.

[6]Note that all our restrictions are also satisfied when we introduce wage stickiness. We assume flexible wages in the baseline set-up to maintain the model as simple as possible and leave aside all the unnecessary complications. The restrictions are also satisfied when we increase the persistence of wage bargaining shocks to higher values (usually not considered in the literature). In addition, our results are confirmed also in a medium-scale version of the model with capital accumulation and real rigidities. All results are available upon request (FOOTNOTE NOT INTENDED FOR PUBLICATION).

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 while 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.[7]

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 in the long run (both for output and unemployment). In Figures 6 and 7 we present the impulse response functions for the 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 identifying labor supply and technology shocks. The median response of unemployment is positive for the first three quarters before turning negative.

[7] As discussed in Fry and Pagan (2011), a variance decomposition based on the median of the impulse responses combines information stemming from several models so that it does not necessarily sum to one across all shocks. As in Furlanetto, Ravazzolo and Sarferaz (2014), our variance decomposition measure is rescaled such that the variance is exhaustively accounted for by our four shocks. In Section 4.2 we consider an alternative measure of central tendency in which the variance decomposition does not require any normalization.

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, at least as long as labor supply shocks capture the large changes over time in demographics, family structure, and female labor force participation, as discussed in Rogerson (2012).

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 bargaining shocks). In Shapiro and Watson (1988) the labor market shock explains on average 40 percent of output fluctuations at different horizons and 60 percent of short-term fluctuations in hours (80 percent in the long run). In Blanchard and Diamond (1989) shocks to the labor force explain 33 percent of unemployment volatility in the very short run and around 15 percent 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 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 play a significant role in macroeconomic dynamics.

Our results are also related to previous theoretical studies in the business cycle 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 has been interpreted either as an efficient shock to preferences or as an inefficient wage mark-up shock (cf. Smets and Wouters, 2007). Since 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 mark-up 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. 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 mark-up shocks. Not surprisingly, they find that wage mark-up shocks account for 80 to 90 percent of unemployment fluctuations at a 40-quarter horizon. Our findings suggest that shocks generating the type of co-movements between variables that are typically associated with wage mark-up 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 on the role of wage mark-up shocks made in the aforementioned papers.

While we concentrate our interest on labor market shocks, our baseline VAR 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, in keeping with previous VAR studies (cf. Furlanetto, Ravazzolo and Sarferaz, 2014) but in contrast with the predictions of standard DSGE models (cf. Smets and Wouters, 2007). 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. The fact that productivity shocks have a large effect on real wages and a limited effect on unemployment is consistent with most models with search and matching frictions driven by productivity shocks. Therefore, our results suggest that 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, as it is the case in our VAR model.

The responses of real wages to demand shocks and of unemployment to technology shocks are left unrestricted in our identification scheme. Therefore, the VAR may provide some new empirical evidence on these conditional responses of variables that have received some attention in the 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. 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, and Mumtaz and Zanetti, 2012), but it is in contrast with the evidence presented in most VAR models identified with long-run restrictions (cf. Galí, 1999).

4.2 Sensitivity analysis

In Figures 10 and 11, we provide the variance decomposition for output and unemployment in a series of robustness checks.

In the first row of Figure 10 we expand the sample by using data over the period 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 assumptions 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.

In the second row of Figure 10 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 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. 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 a different measure of central tendency such as the median target proposed by Fry and Pagan (2011).[8] 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.

In the first row of Figure 11 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 parameterizations characterized by a high degree of price stickiness and interest rate smoothing. However, the response of real wages is almost always positive at horizon two. Here we take the model at face value and we impose the restrictions on real wages at quarter two rather than on impact. The results are basically unaffected.

In the third row of Figure 11 we modify the lag length in the estimation. In our baseline we follow the standard practice of using five lags for quarterly series. Here we estimate the model with two lags, which is the optimal lag length suggested by the SIC criterion, and we find that our results are confirmed.[9]

To sum up, the main result emerging from these experiments is that the *joint* importance of the labor market shocks is somewhat lower (although still far from being

[8]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.

[9]Following the paper of Ivanov and Kilian (2005), the most accurate criterion for quarterly VAR models with roughly 120 observations is the SIC. We also confirm the same results when we consider the lag length selected according to the AIC criterion.

negligible) when we extend or reduce the sample period. However, the two shocks remain of comparable importance across the different experiments (with a larger role for wage bargaining shocks in the short term and a larger role for labor supply shocks at low frequencies).

4.3 Discussion of sign reversals

In our baseline model VAR model we rely on the minimum amount of restrictions necessary for identification without imposing any additional structure. However, the fact that the restrictions are imposed only on impact opens the door to sign reversals that may be hard to interpret. An example of such a case is the response of unemployment to an expansionary labor supply shock that turns negative after three quarters (cf. Figure 6) in line with the unconditional correlation between output and unemployment which is negative. The reader may then think that labor supply shocks turn out to be important in our set-up only because identification is too weak and the sign reversal brings the sign of the conditional correlation between output and unemployment in line with the sign of the unconditional correlation. We now address this possible criticism from two angles.

First, we impose the sign restriction on unemployment over a longer horizon (four quarters) with the goal of limiting the scope for sign reversals. We see in the second row of Figure 11 that labor supply shocks maintain an important role in such a set-up and our results are almost unchanged.

Second, we reconsider the response of unemployment to a labor supply shock from a theoretical perspective to show that the sign reversal can be given a structural interpretation using the model developed in Section 2. In Figure 12, we plot the range of possible responses of labor market variables to a labor supply shock in the baseline case and when prices are flexible. As emphasized in Section 3.3, a positive labor supply shock leads to an increase in the number of participants and in the number of people looking for a job. As a consequence, the labor market slackens, it becomes easier for firms to recruit and job creation picks up. Since the increase in labor force participation is very persistent, the increase in job creation is not strong enough to offset the increase in the number of job seekers and unemployment increases on impact before going back slowly to steady-state. Nevertheless, we see that for a non-negligible share of parameterizations the convergence to steady-state is non-monotonic, thus featuring a sign reversal. This reflects a boom in vacancy posting that lead to an increase in employment that is even larger than the increase in participation in period two. Importantly, the sign reversal is more likely in the presence of flexible prices. In that case, markups do not increase following the shock. As a result, the expected benefits of having a filled vacancy do not decrease as much as when prices are sticky and the pick up in vacancy posting is stronger. Unemployment still increases on impact in all cases, but it undershoots its steady-state value from period two onwards for a large share of parameterizations. We conclude that the theoretical model can generate a sign reversal for unemployment in response to a labor supply shock, at least for some parameterizations.

5 Introducing data on the participation rate

In the previous section we 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. As in the estimated model by Galí, Smets and Wouters (2011), 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 almost all the parameterizations of the model we consider (cf. Figure 4).

We introduce the participation rate in the VAR to take advantage of the additional restrictions. We also include a fifth shock 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.[10] The restrictions are

[10]In Appendix 4 we consider the price mark-up shock as a fifth shock in the model by introducing

summarized in Table 3.

Table 3: Sign restrictions

	Demand	Technology	Labor Supply	Wage Bargaining
GDP	+	+	+	+
Prices	+	-	-	-
Real wages	/	+	-	-
Unemployment	-	/	+	-
Participation	/	/	+	-

In Figure 13 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 in the decomposition of 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, 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 14 we plot the impulse responses of the participation rate to the four identified shocks.[11] 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).[12] 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).[13]

additional restrictions on the behavior of the participation rate.

[11]The impulse responses for the other variables are very similar to the ones derived in the baseline model. (FOOTNOTE NOT INTENDED FOR PUBLICATION)

[12]This sign reversal cannot be generated by our simple model. However, a medium-scale version of the model with capital accumulation, sticky wages an real rigidities delivers these dynamics under reasonable parameterizations. (FOOTNOTE NOT INTENDED FOR PUBLICATION)

[13]The evidence on the response of participation to technology shocks is mixed: it is countercyclical in Galí (2011) unlike in Christiano, Trabandt and Walentin (2012) where it is procyclical. Both papers identify technology shocks using long-run restrictions, but the exact specification of the models differ. Christiano, Trabandt and Walentin (2012) include more variables in their analysis and identify more shocks. Our results weakly support a procyclical response. Further discussion on this point is provided in Appendix 4.

Our model can also be used to investigate the historical evolution of the participation rate, with a special focus on recent years. It is well known that the participation rate has been steadily increasing over time until the very end of the 1990s. Since then, it has been gently declining with an acceleration from 2008 onwards (cf. the solid line in Figure 15 where the 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 (cf. the dark blue area in Figure 15).[14] 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 in recent years.

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, among others). Under this view ("the bad omen view" in the words of Bullard, 2014) the decline of the unemployment rate over the latest 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 demographic groups have different propensities to participate (cf. Fujita, 2014; Kudlyak, 2013; 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 explains 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 same ballpark as BLS projections

[14] This reflects the influence of the initial conditions. As discussed in Giannone, Primiceri and Lenza (2014), flat-prior VARs tend to attribute an implausibly large share of the variation in macroeconomic variables to the deterministic (and entirely predictable) component. We remark that the role of initial conditions for participation dynamics is relatively modest in our model, despite the participation rate being a relatively predictable variable.

(according to which more than 70 percent of the decline is due to purely demographic factors) and Fujita (2014) who finds that about 65 percent of the decline in participation is due to retirements and disability.

However, 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 (2015), 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). They 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 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. Barnichon and Figura (2015) find that this labor supply shift can account for 1.75 percentage points of the decline in participation, whereas the demographic factors account for an additional 1.5 percentage points. They suggest three possible interpretations for this negative labor supply shift: i) a reduction in the added-worker effect driven by the strong wage growth of the second half of the 1990s, 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 showed 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 saw 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 further disentangle 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 16 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 17 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. 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 also captures 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, 2016). When the degree of price rigidity is high, firms cannot decrease prices as much as they would like to: the expansion in aggregate demand is less pronounced and firms do not need necessarily to post more vacancies to produce the quantities demanded. Thus, the impact response of vacancies can be either positive or negative in our model, as shown in Figure 17. However, the response of vacancies is unambiguously negative in period two, even for moderate degrees of price stickiness.[15] In contrast, wage bargaining shocks move unemployment and vacancies in opposite directions both on impact and in period two, as shown in Figure 4. Therefore, we can go one step further in the analysis by introducing data on vacancies in our VAR

[15]Benati and Lubik (2014) show that separation rate shocks also move unemployment and vacancies in the same direction. Both matching efficiency and separation shocks have been considered as examples of reallocation shocks in the literature and both shocks are consistent with our identification assumptions under general conditions.

and by using the asymmetric response of this variable in response to wage bargaining and matching efficiency shocks to disentangle these two forces. The restrictions on vacancies are imposed in the second period in keeping with the prediction of the theoretical model, as detailed in Table 4.

Table 4: Sign restrictions

	Demand	Technology	Labor Supply	Wage Bargaining	Matching Efficiency
GDP	+	+	+	+	+
Prices	+	-	-	-	-
Real wages	/	+	-	-	-
Unemployment	-	/	+	-	-
Vacancies	/	/	/	+	-

In Figure 18, we plot the variance decomposition of this extended model. While the contributions of demand and technology shocks to economic volatility are mostly unchanged, labor supply and wage bargaining shocks now account for a more modest share of fluctuations in output and unemployment. The contribution of matching efficiency shocks to the variance of the different variables is substantial. Our analysis here suggests that wage bargaining shocks, that are often important in macroeconomic models, may capture the effects of reallocation shocks (and perhaps shocks to the unemployment benefits) more than variations in unions' bargaining power. Notice that it is crucial to rely on a model with search and matching frictions to disentangle wage bargaining shocks from reallocation shocks.

In Figure 19 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 for a few quarters. This is imposed as an identification assumption for matching efficiency shocks but not for labor supply shocks, whose effect on vacancies is ambiguous in the context of the theoretical model. A contractionary labor supply shock lowers both unemployment and vacancies on impact (thus shifting the Beveridge curve inward) but the effect on vacancies is quickly reversed. Therefore, our analysis adds one additional element to the debate on the outward shift of the Beveridge curve observed in the immediate aftermath of the Great Recession: while a negative matching efficiency shock triggers an outward shift of the Beveridge curve, a negative labor supply shock generates an inward shift on impact and then generate dynamics along the curve in the south-east direction (cf. impulse responses in Figure 19). These results lead us to two considerations. First, negative matching efficiency shocks are a promising explanation to rationalize the outward shift in the Beveridge curve observed in the aftermath of the Great Recession. Second, negative labor supply shocks cannot explain the outward shift of the Beveridge curve (in fact they imply a short-lived inward shift) but can explain why the recovery has been so sluggish through movements along the Beveridge curve leading to lower vacancy posting and higher unemployment. As far as we know, these dimensions have so far been neglected in the debate.

7 Conclusion

The objective of this paper is to identify labor supply shocks separately from other shocks originating in the labor market in the context of a sign restricted VAR. To achieve our goal we impose theory-based sign restrictions on the responses of the unemployment rate and the participation rate to shocks. We find that the importance of wage bargaining shocks is larger in the short run, while labor supply shocks are crucial to capture macroeconomic dynamics in the long run. However, both shocks have a quantitatively relevant impact both in the short run and the long run. Therefore, disentangling these shocks is important. Our results suggest that polar assumptions on the role of labor market shocks (i.e. assuming that one of the shocks is irrelevant in the long run, in the short run or at any horizon) often made in the DSGE literature may be misguided.

While the two shocks are of comparable importance across different specifications, their joint importance is magnified by the presence of the Great Recession in our sample period. Nevertheless, even when we extend or reduce the sample period, the role of labor market shocks remains substantial, in keeping with previous contributions starting with Shapiro and Watson (1988) and Blanchard and Diamond (1989). While the structural interpretation of these shocks is still debatable, our paper suggests that they should not be dismissed as potential drivers of business cycle fluctuations. In that sense, the fact that labor market shocks prove to be important in estimated New Keynesian models (as in Smets and Wouters, 2007) is not necessarily problematic.

Finally, in this paper we have made some progresses in the interpretation of wage bargaining shocks by showing that they are also likely to capture variations in unemployment benefits and shifts in matching efficiency. We believe that further refining the interpretation of labor supply shocks may be an interesting avenue for future research. In particular, disentangling demographic factors from the declining desire to work among non-participants, and perhaps also the role of immigration in labor supply dynamics, are potential extensions that we may consider in the future.

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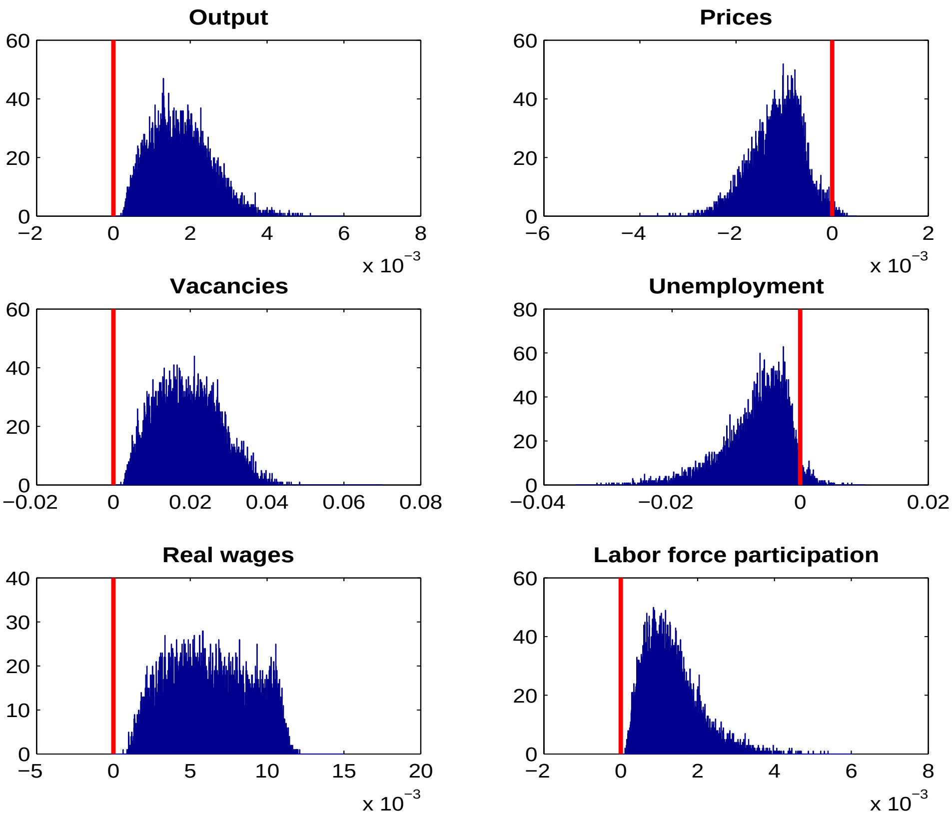

Figure 1: Distribution of impact responses to a 1% risk premium shock.

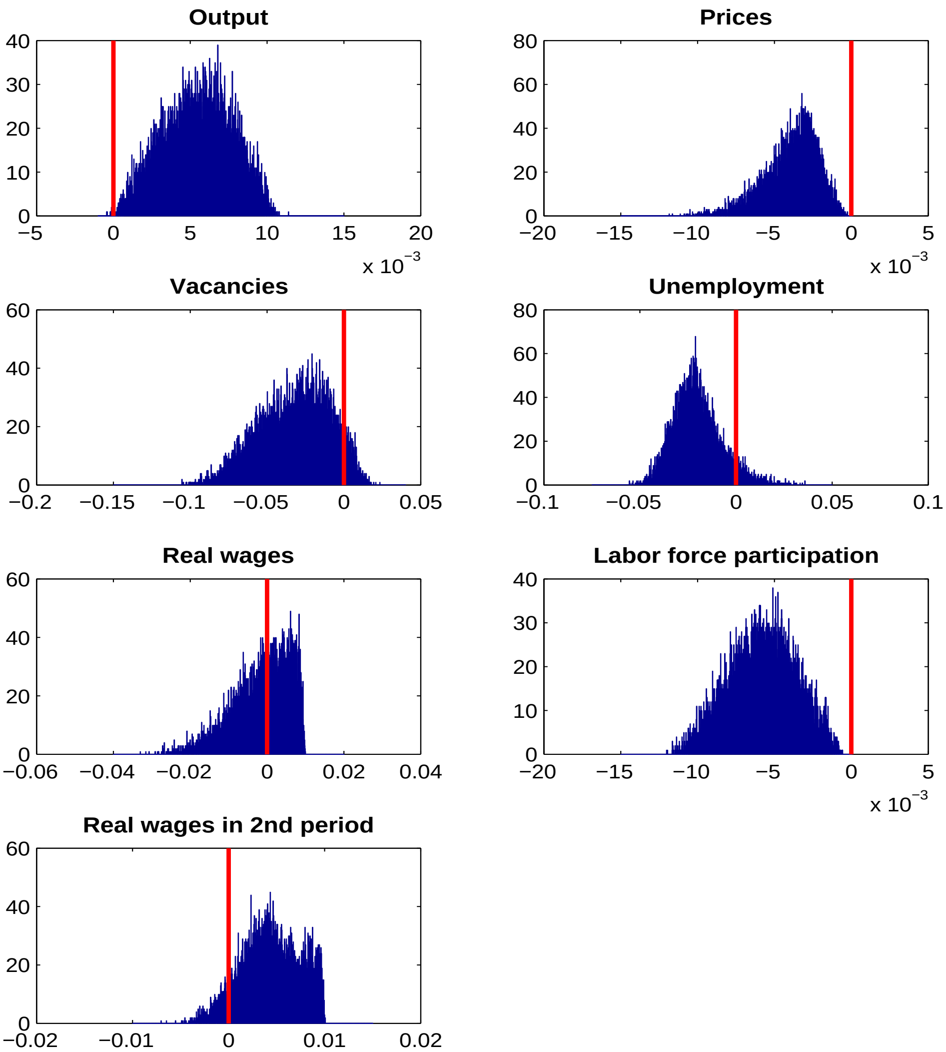

Figure 2: Distribution of impact responses to a 1% technology shock.

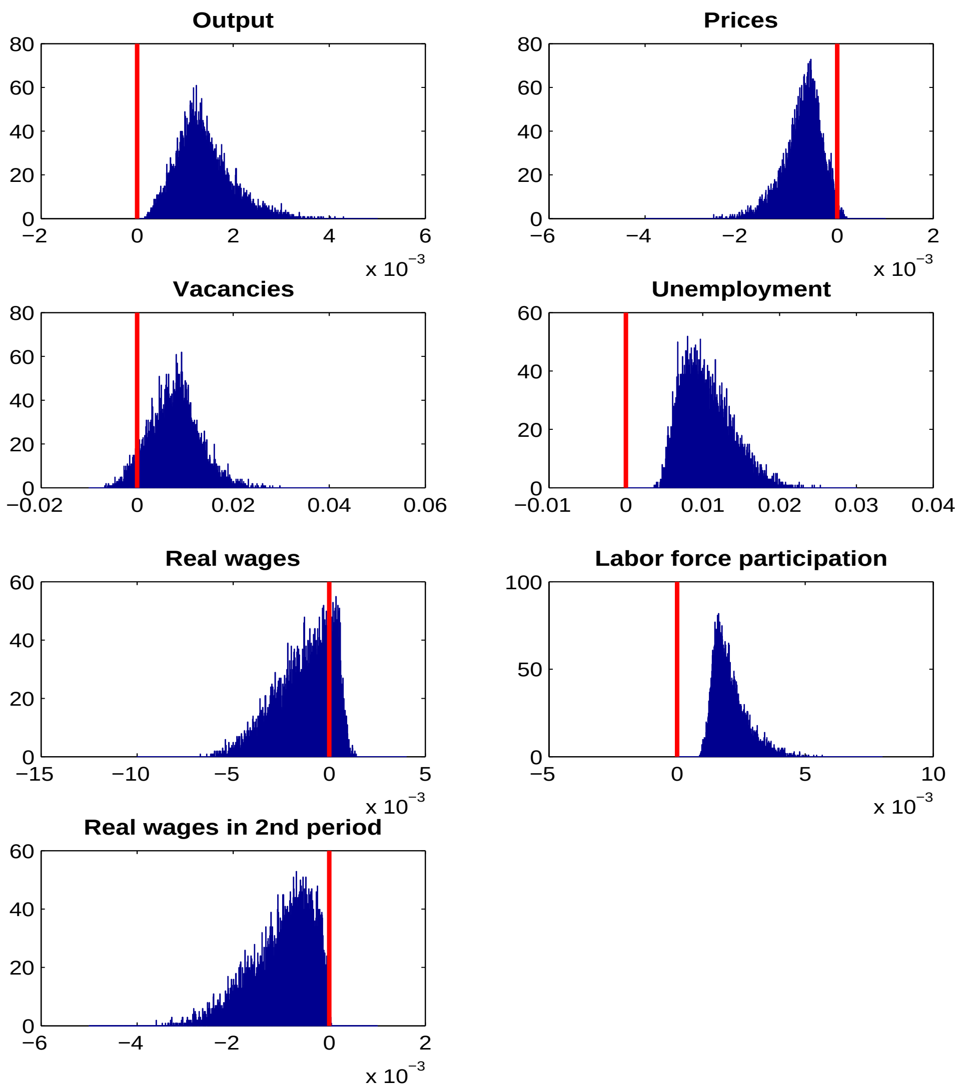

Figure 3: Distribution of impact responses to a 1% labor supply shock.

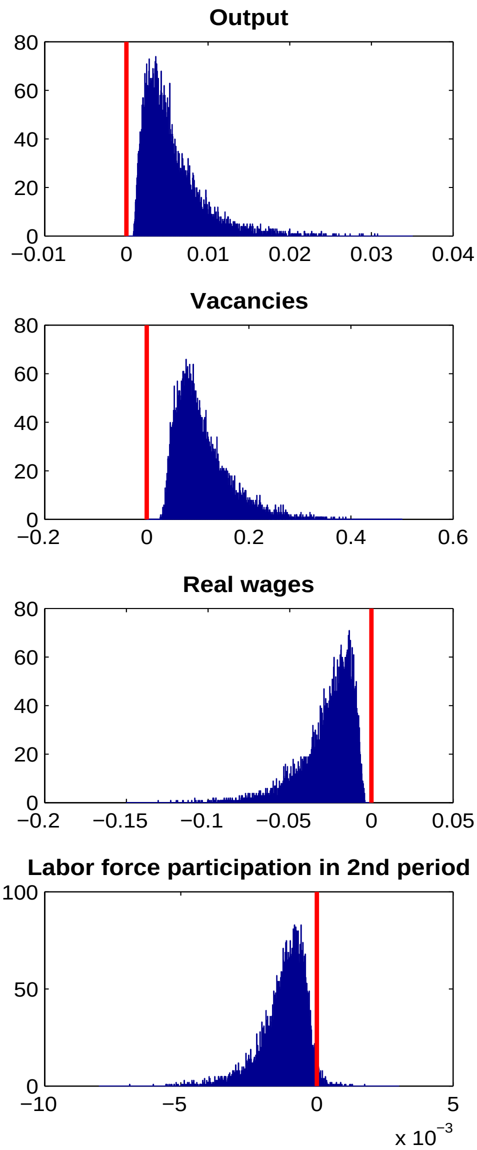

Figure 4: Distribution of impact responses to a 1% wage bargaining shock.

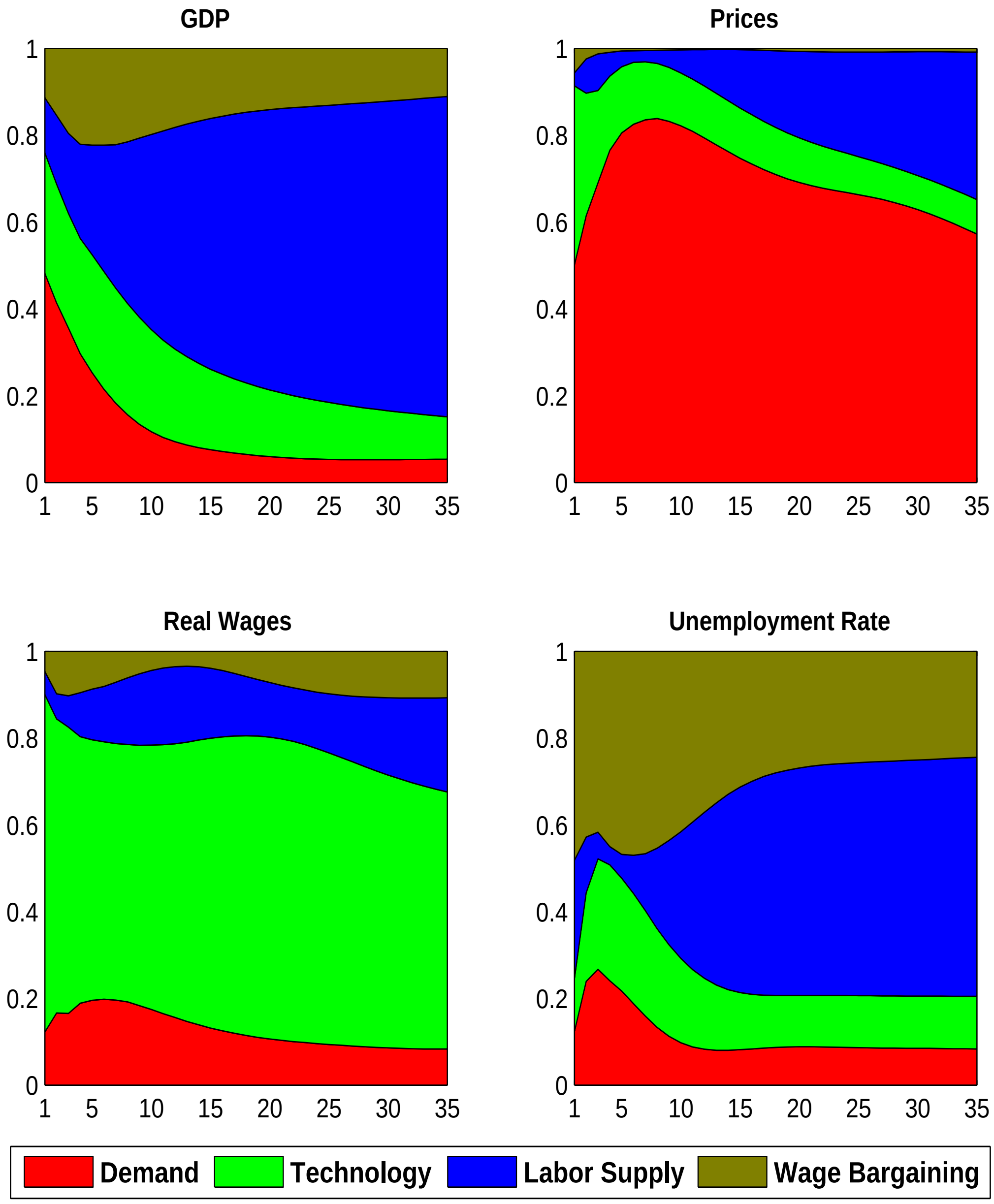

Figure 5: Variance decomposition for the baseline VAR model

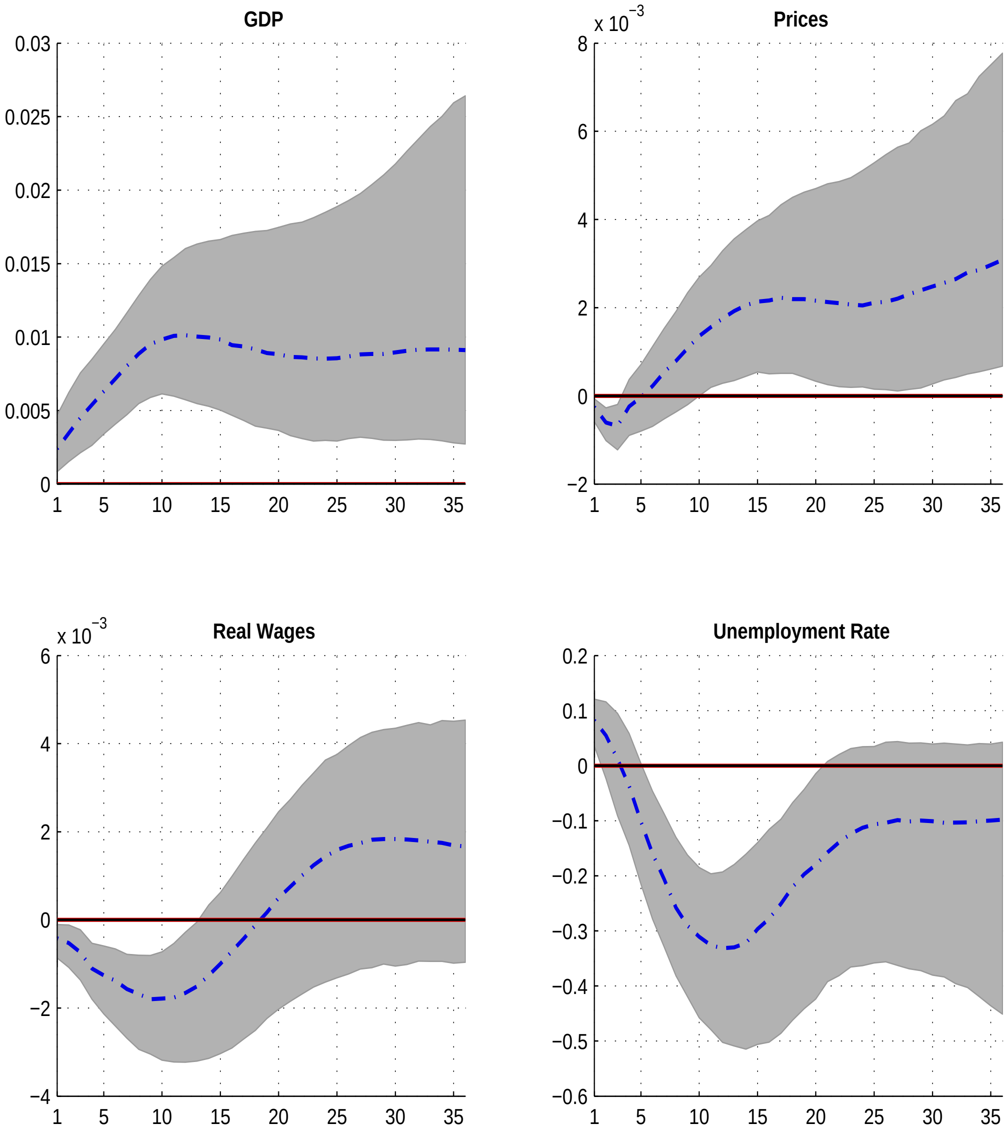

Figure 6: Impulse responses to a labor supply shock in the baseline VAR model. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 16th and 84th percentiles of the impulse responses.

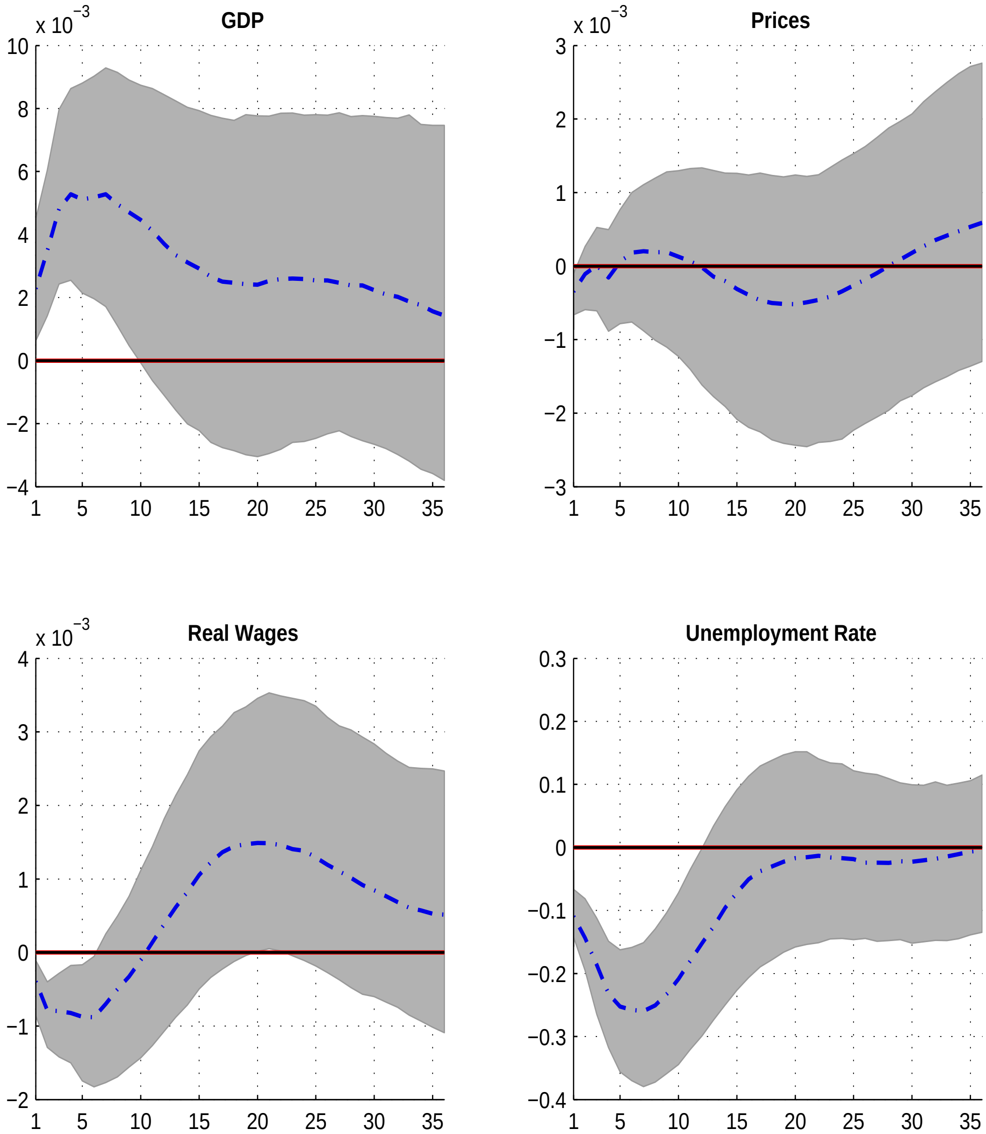

Figure 7: Impulse responses to a wage bargaining shock in the baseline VAR model. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 16th and 84th percentiles of the impulse responses.

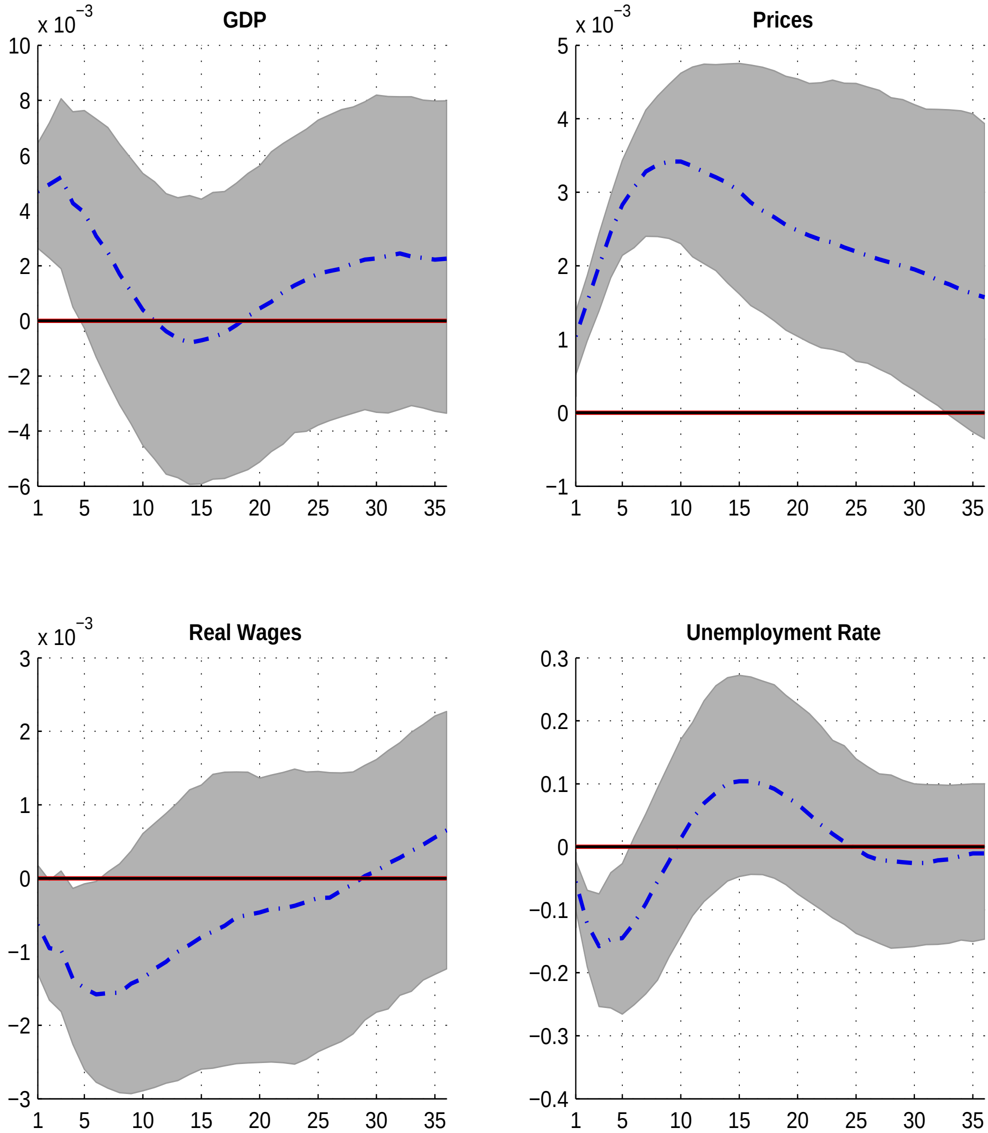

Figure 8: Impulse responses to a demand shock in the baseline VAR model. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 16th and 84th percentiles of the impulse responses.

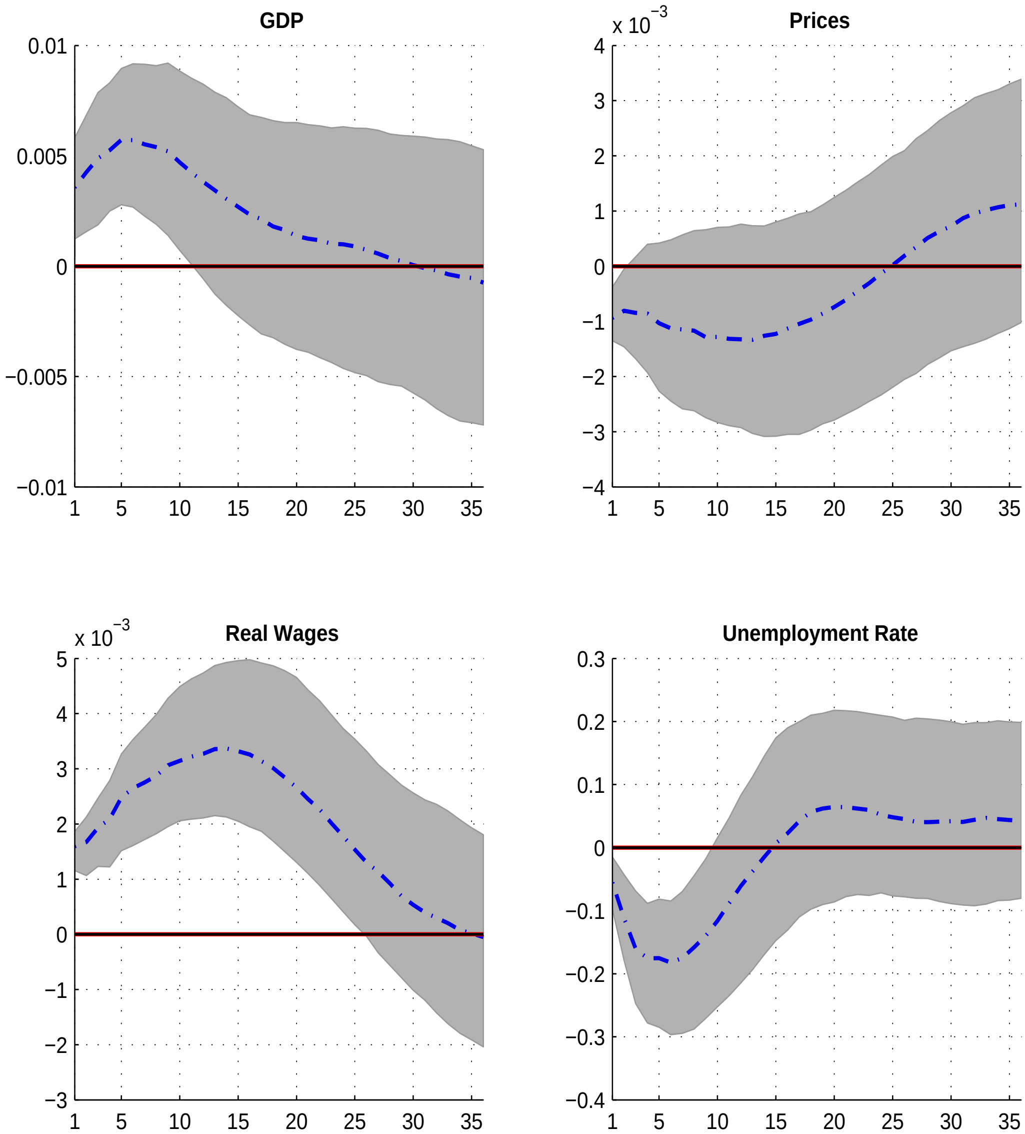

Figure 9: Impulse responses to a technology shock in the baseline VAR model. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 16th and 84th percentiles of the impulse responses.

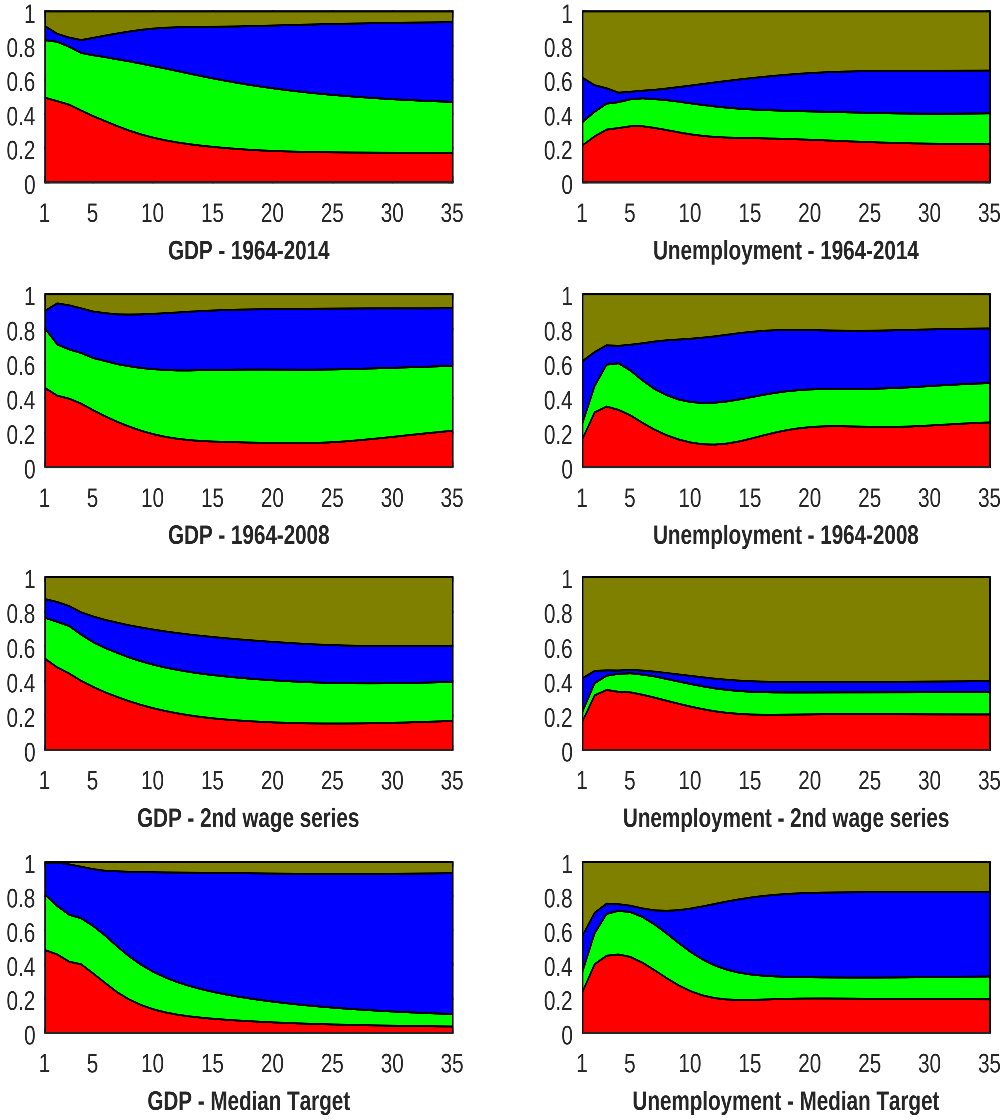

Figure 10: Sensitivity analysis for the baseline VAR model - 1.

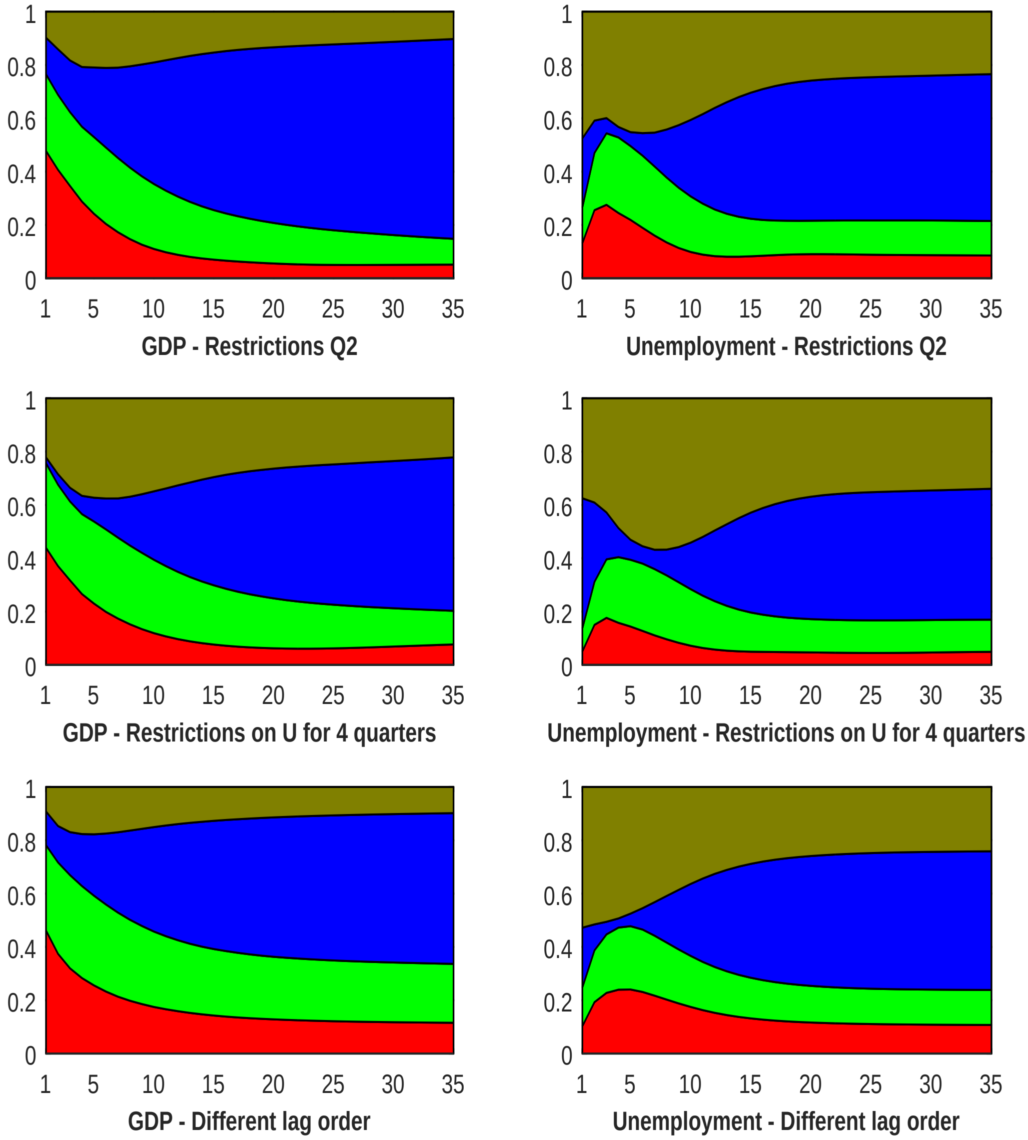

Figure 11: Sensitivity analysis for the baseline VAR model - 2.

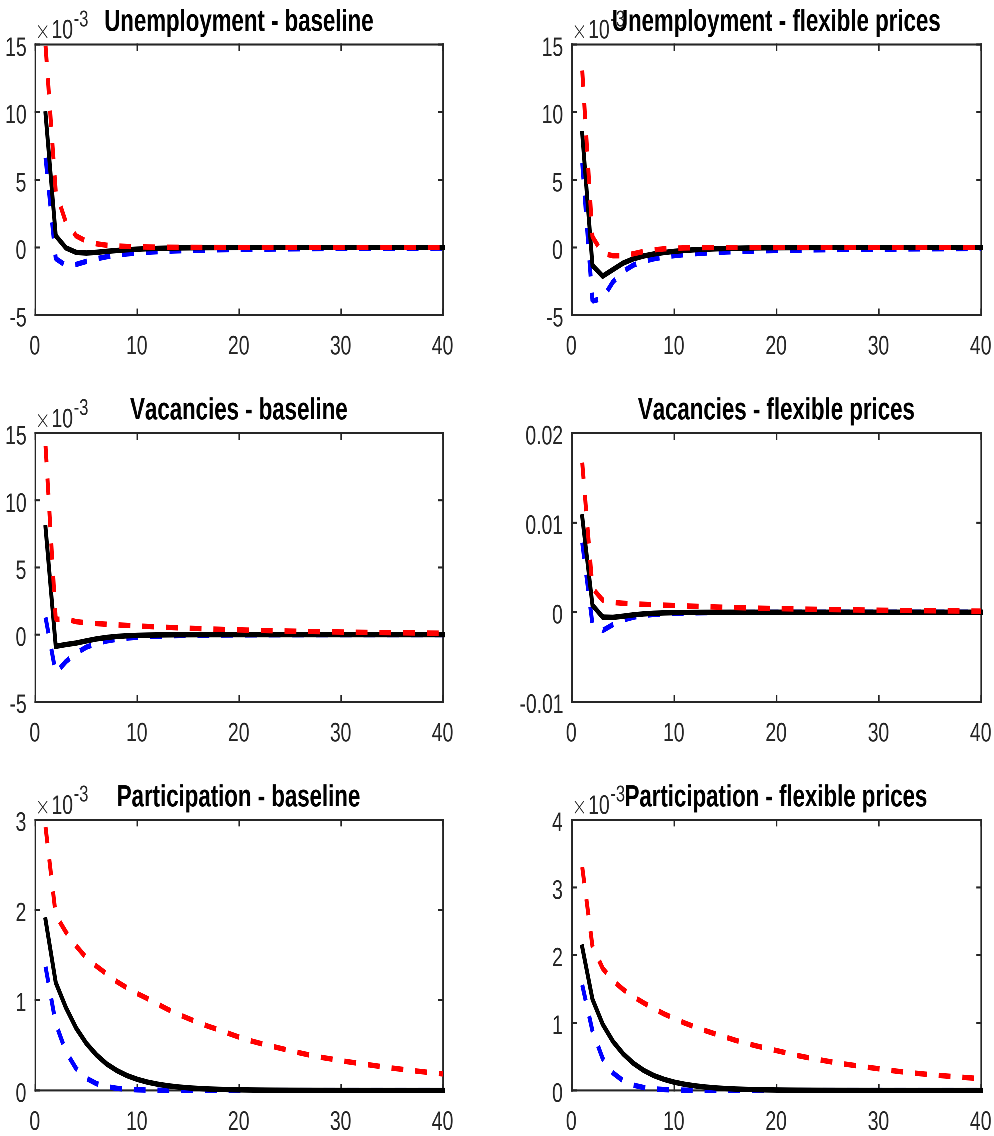

Figure 12: Distribution of impulse responses to a 1% labor supply shock in the theoretical model under the baseline parameterization (left column) and under flexible prices (right column). The black solid line represents the median across the 10000 parameterizations at each horizon, the blue dashed line indicates the 10th percentile and the red dashed line the 90th percentile.

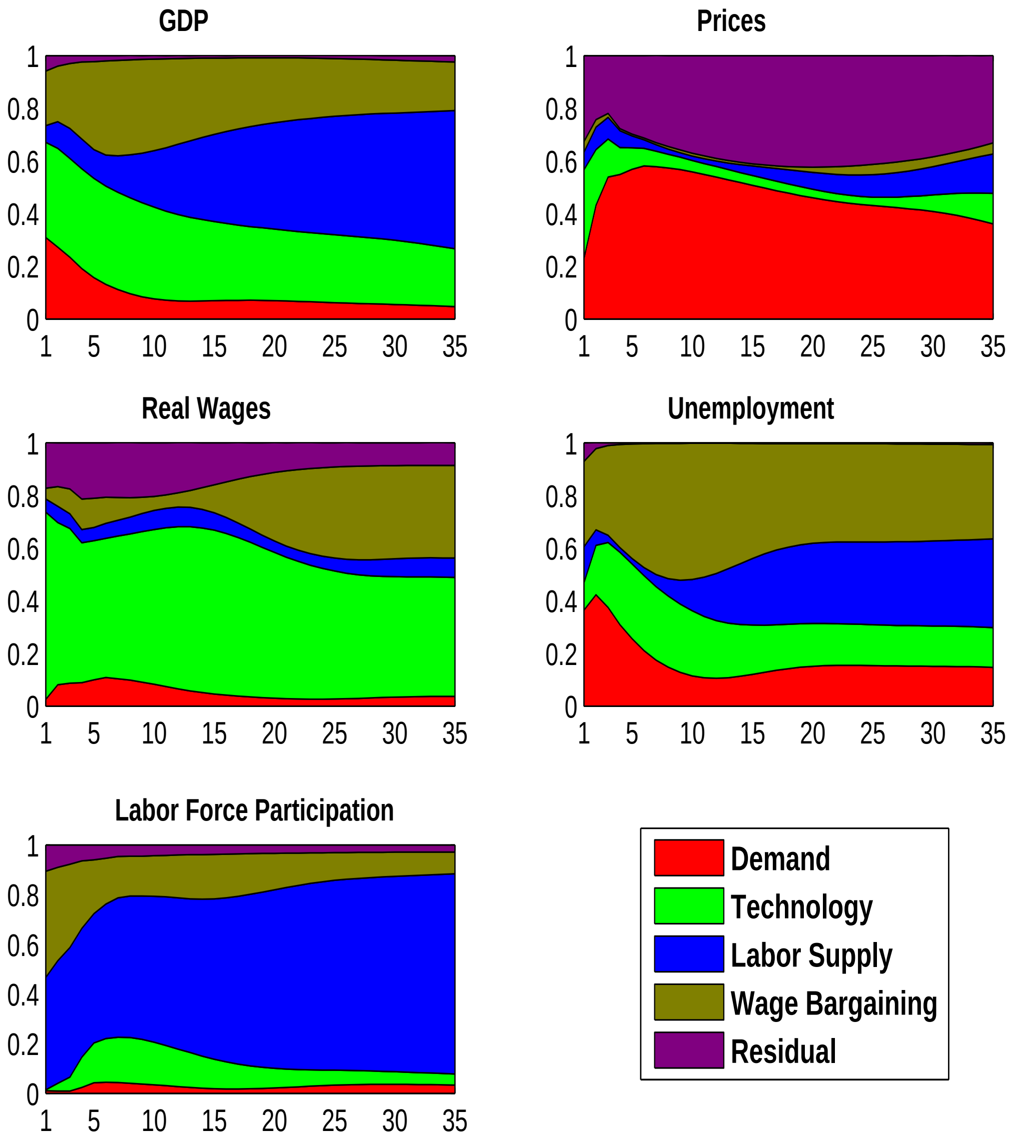

Figure 13: Variance decomposition for the extended VAR model with data on labor force participation.

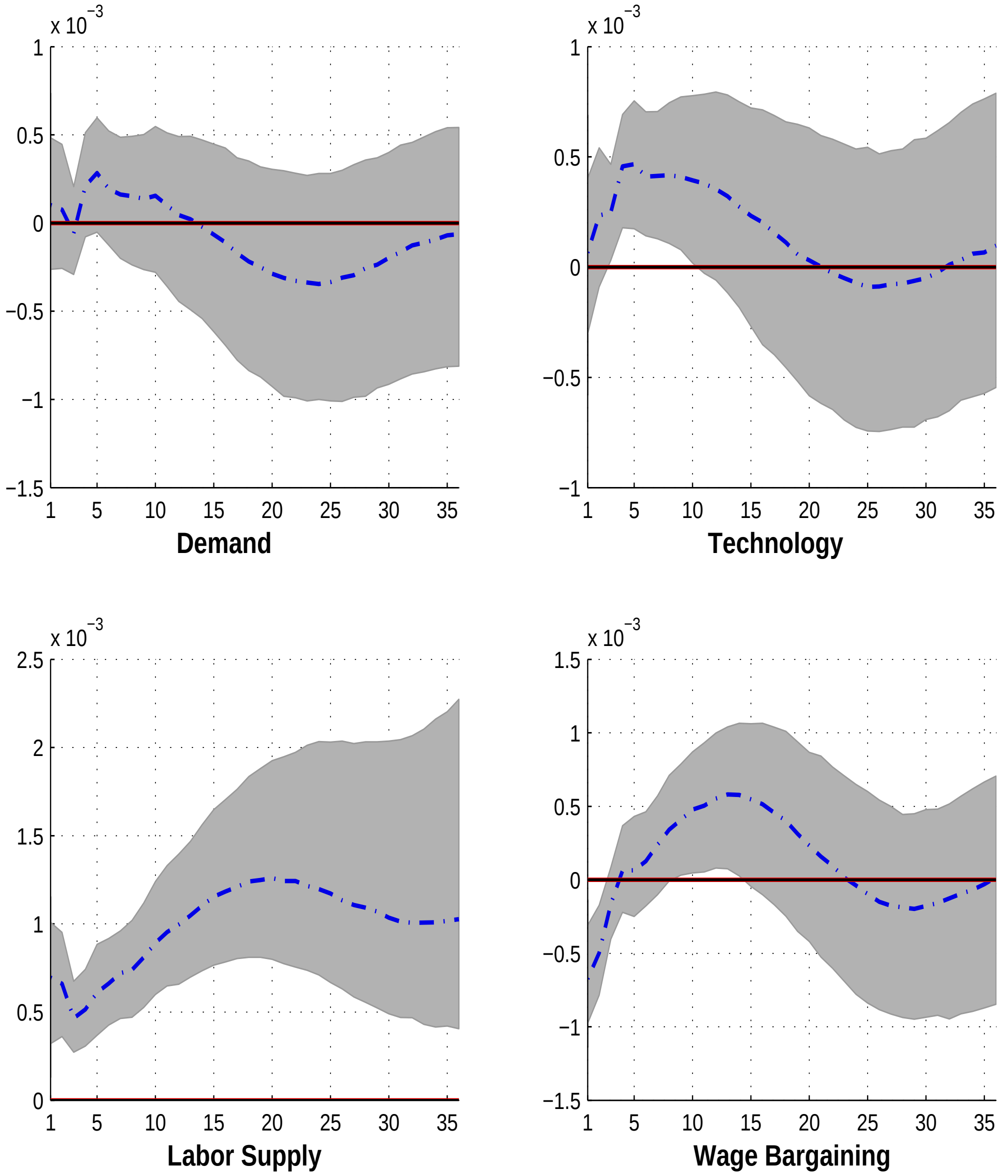

Figure 14: Impulse responses of the participation rate to the four identified shocks. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 16th and 84th percentiles of the impulse responses.

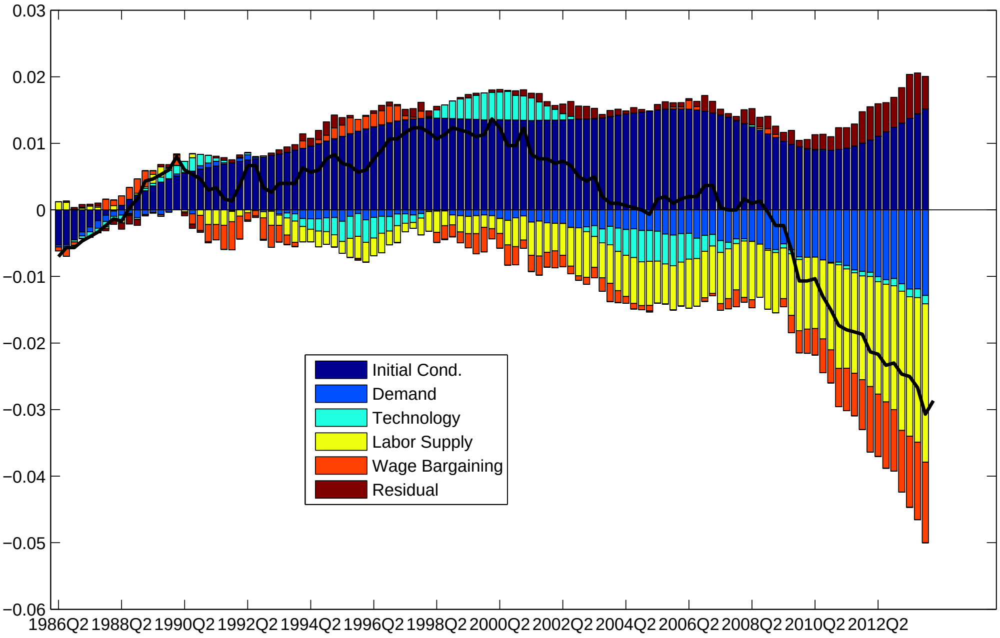

Figure 15: Historical decomposition for the labor force participation rate in deviation from its mean (solid line).

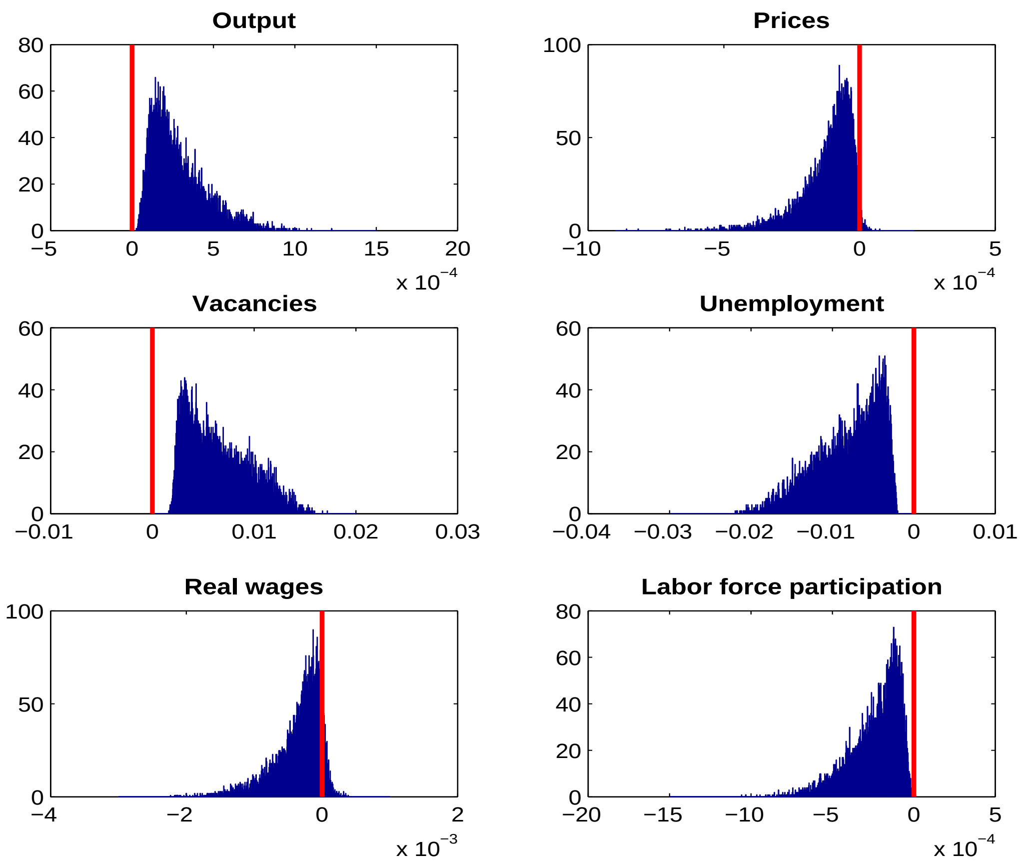

Figure 16: Distribution of impact responses to a 1% unemployment benefit shock.

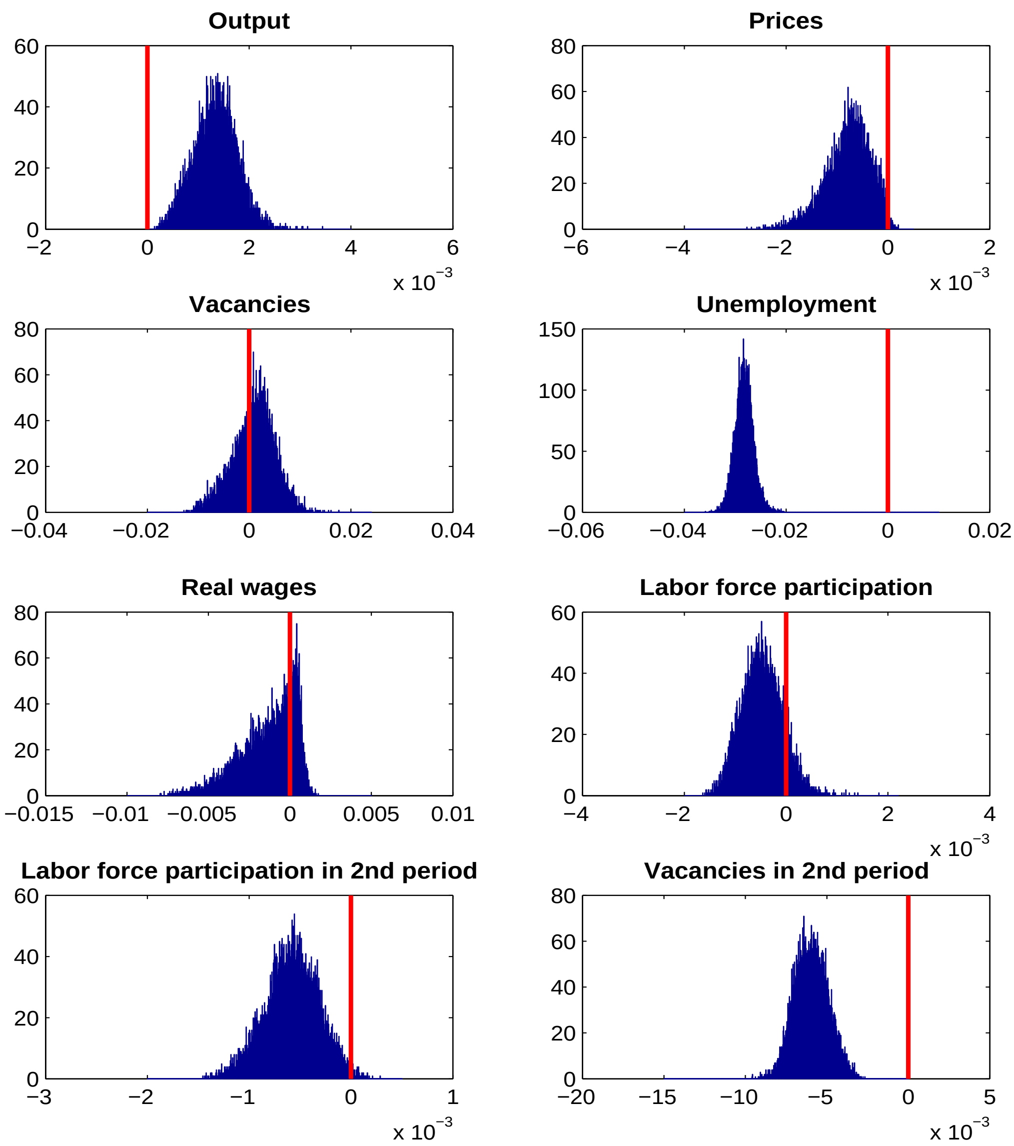

Figure 17: Distribution of impact responses to a 1% matching efficiency shock.

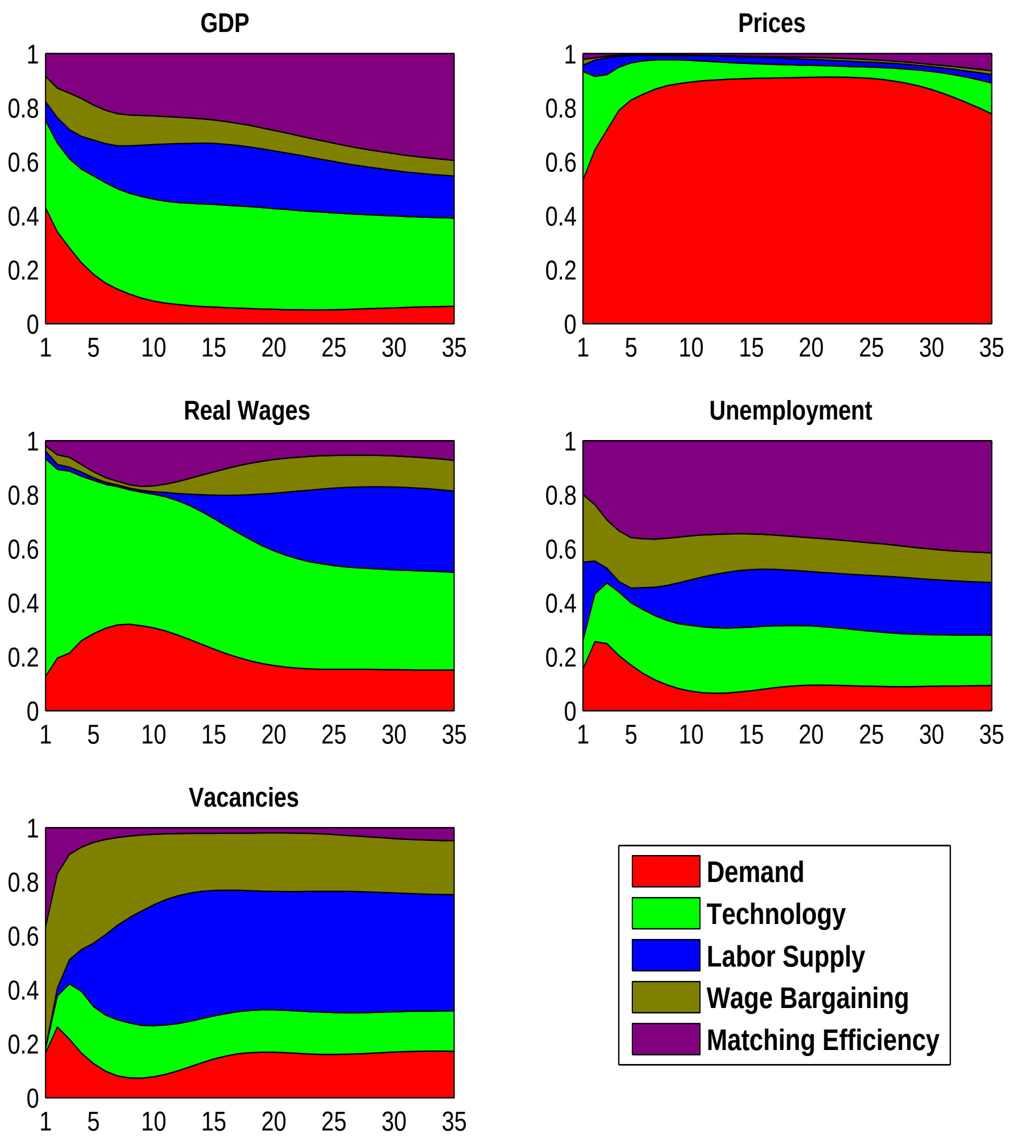

Figure 18: Variance decomposition in VAR model extended with data on vacancies.

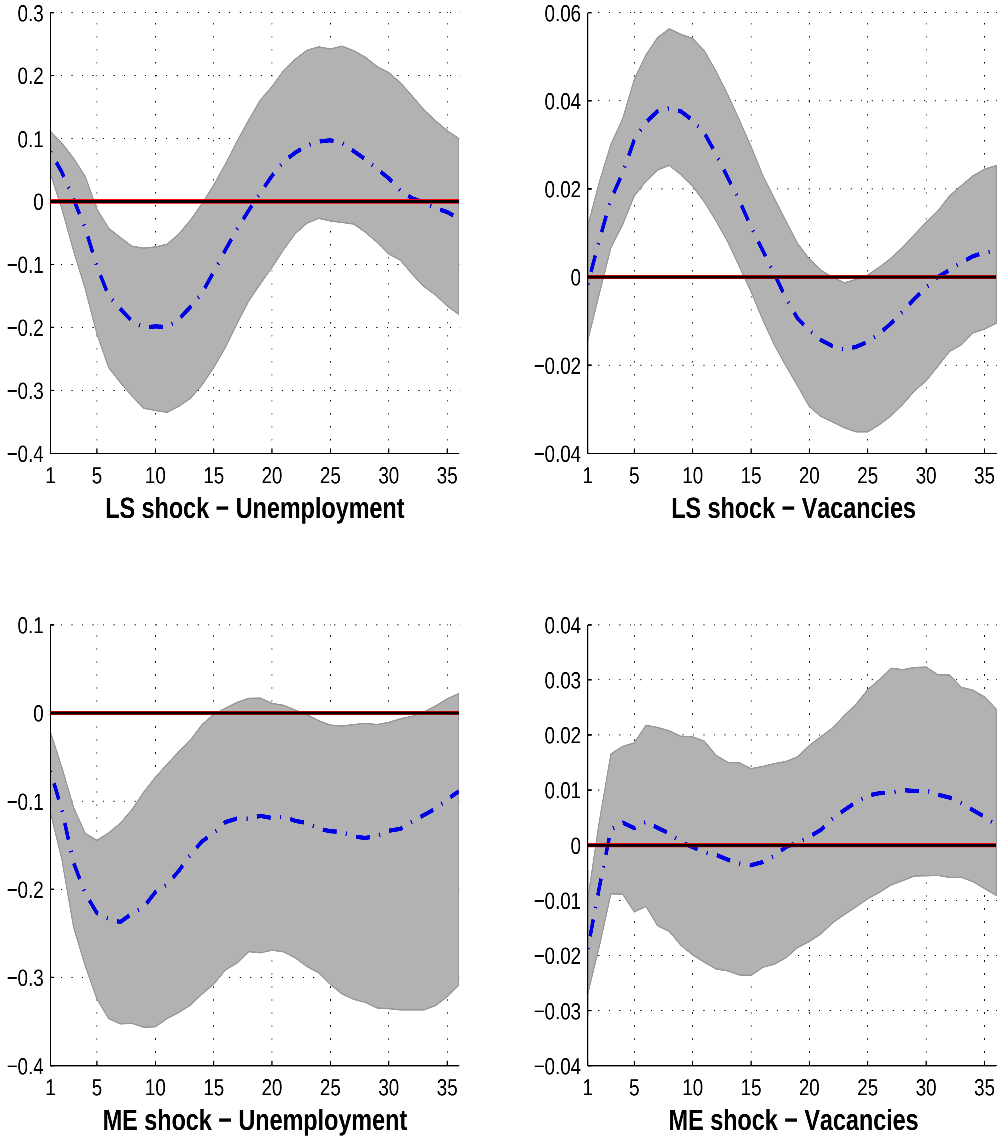

Figure 19: Impulse responses of unemployment and vacancies to labor supply and matching efficiency shocks. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 16th and 84th percentiles of the impulse responses.

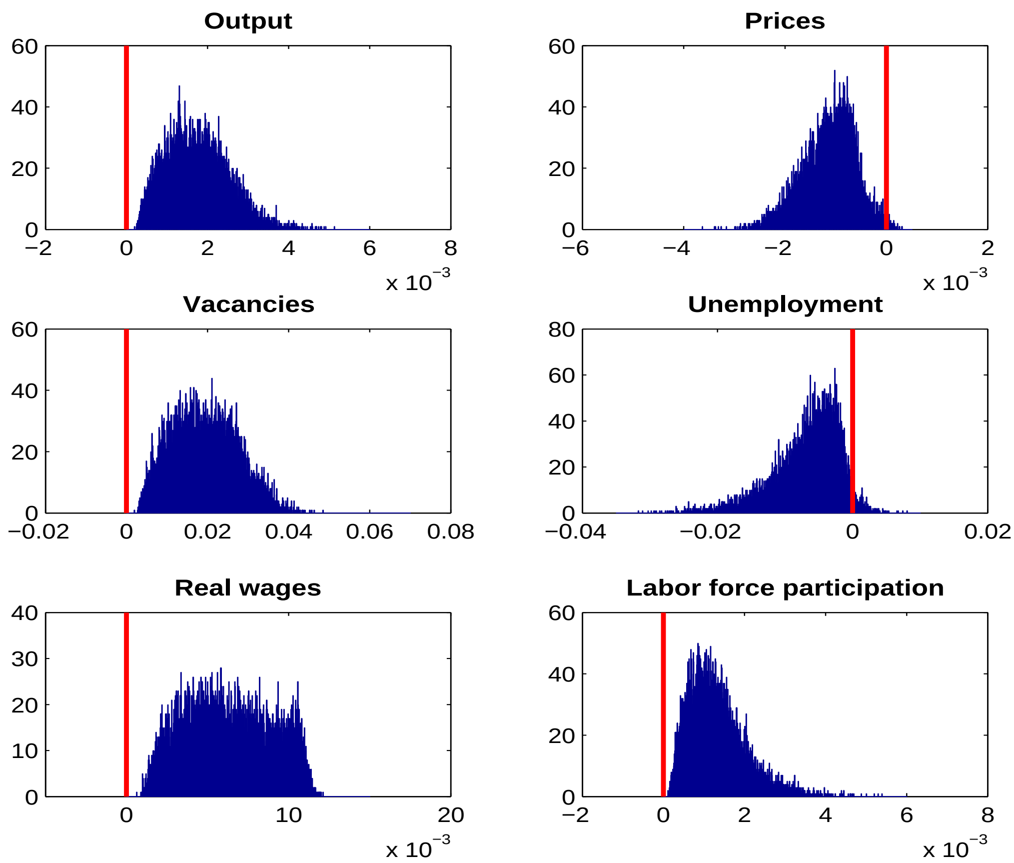

Figure 20: Distribution of impact responses to a 1% price markup shock.

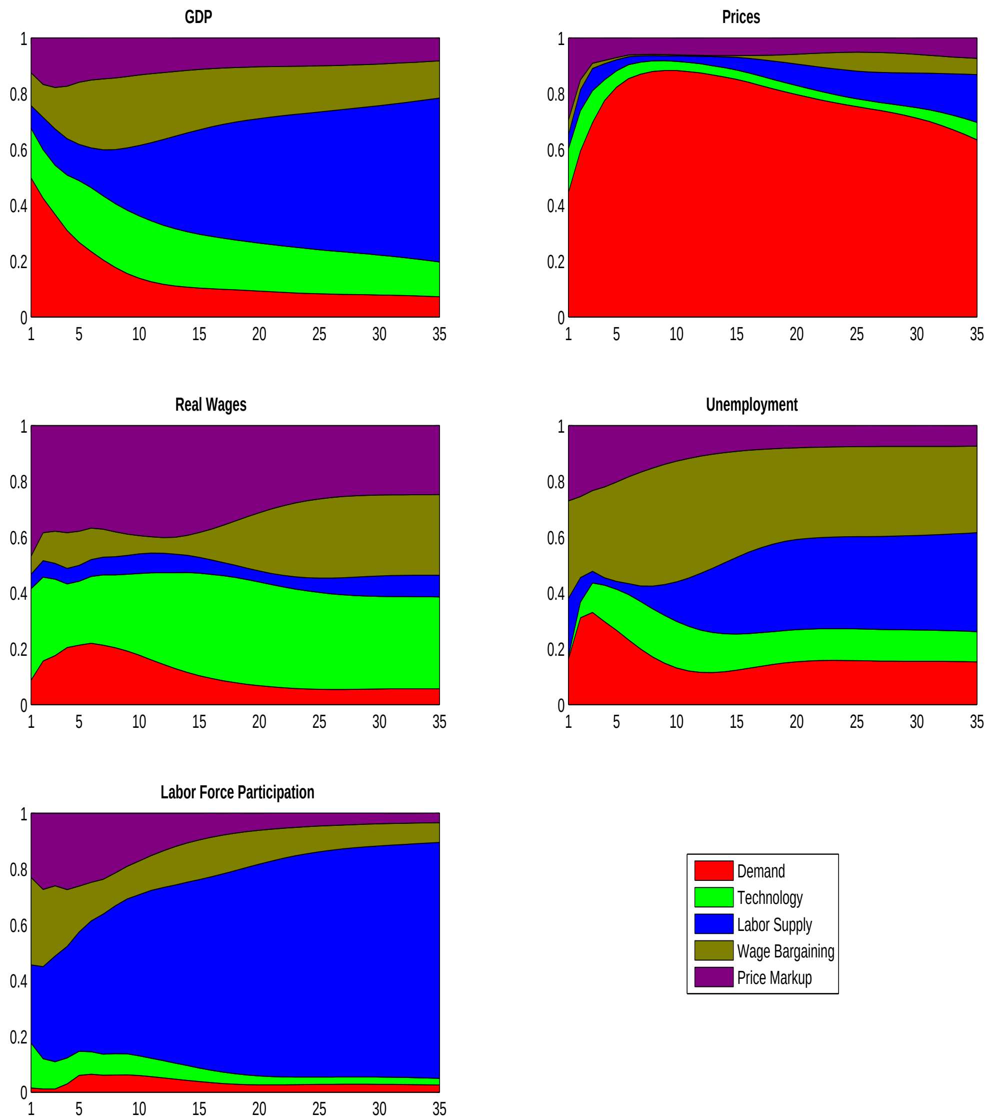

Figure 21: Variance decomposition in VAR model extended with price-markup shocks.

A Appendix

A.1 Log-linear equations characterizing the decentralized equilibrium

- $c_t = E_t c_{t+1} - \frac{1}{\sigma}(r_t - E_t \pi_{t+1} + \varepsilon_t^p)$

- $\frac{\kappa}{\Gamma}\theta^{\alpha}\left(\alpha\theta_t - \gamma_t\right) = \frac{Z}{\mu}(z_t - \mu_t) - ww_t + \beta(1-\rho)\frac{\kappa}{\Gamma}\theta^{\alpha}\left(\sigma c_t - \sigma E_t c_{t+1} + \alpha E_t \theta_{t+1} - E_t \gamma_{t+1}\right)$

- $ww_t = bb_t + \frac{\eta}{1-\eta}\frac{\kappa}{\Gamma}\theta^{\alpha}\left[\frac{\varepsilon_t^{\eta}}{1-\eta} - \gamma_t + \alpha\theta_t\right] - \beta(1-\rho)\frac{\eta}{1-\eta}\frac{\kappa}{\Gamma}\theta^{\alpha}(1-p)*$
  $\left(\sigma c_t - \sigma E_t c_{t+1} + \frac{\varepsilon_{t+1}^{\eta}}{1-\eta} - E_t\gamma_{t+1} + \alpha E_t \theta_{t+1}\right)\beta(1-\rho)\frac{\eta}{1-\eta}\frac{\kappa}{\Gamma}\theta^{\alpha} p E_t p_{t+1}$

- $\pi_t = \beta E_t \pi_{t+1} - \frac{(1-\beta\delta)(1-\delta)}{\delta}\mu_t - \frac{(1-\beta\delta)(1-\delta)}{\delta}\frac{1}{\varepsilon-1}\varepsilon_t$

- $\chi L^{\varphi} C^{\sigma}\left(\varphi l_t + \sigma c_t + \chi_t\right) = p(w-b)p_t + (1-p)bb_t + pww_t + \beta(1-\rho)(1-p)(\chi L^{\varphi}C^{\sigma} - b)*$
  $(p_t + \sigma c_t) + \beta(1-\rho)\chi L^{\varphi} C^{\sigma}(1-p)E_t\left(\chi_{t+1} + \varphi l_{t+1}\right) - \beta(1-\rho)(\chi L^{\varphi}C^{\sigma} - b)E_t p_{t+1} +$
  $\beta(1-\rho)(1-p)bE_t(\sigma c_{t+1} - b_{t+1})$

- $cc_t + \kappa\theta(L - (1-\rho)N)\theta_t + \kappa\theta L l_t - \kappa(1-\rho)N\theta n_{t-1} = ZN(z_t + n_t)$

- $n_t = (1-\rho)(1-p)n_{t-1} + \frac{pL}{N} l_t + p(\frac{L}{N} - 1 + \rho)p_t$

- $r_t = \phi_r r_{t-1} + (1-\phi_r)\left(\phi_\pi \pi_t + \phi_y y_t\right)$

- $p_t = (1-\alpha)\theta_t + \gamma_t$

- $\eta_t = \varepsilon_t^{\eta}$

- $z_t = \zeta^Z z_{t-1} + \epsilon_t^Z$

- $\varepsilon_t^p = \zeta^p \varepsilon_{t-1}^p + \epsilon_t^p$

- $\varepsilon_t^{\eta} = \zeta^{\eta}\varepsilon_{t-1}^{\eta} + \epsilon_t^{\eta}$

- $\varepsilon_t = \zeta^{\varepsilon}\varepsilon_{t-1} + \epsilon_t^{\varepsilon}$

- $\gamma_t = \zeta^{\Gamma}\gamma_{t-1} + \epsilon_t^{\Gamma}$

- $b_t = \zeta^b b_{t-1} + \epsilon_t^b$

- $\chi_t = \zeta^\chi \chi_{t-1} + \epsilon_t^\chi$

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, aged 16 years and over

- **Civilian labor force participation rate**: taken from the website of the Bureau of Labor Statistics, series ID LNS11300000, seasonally adjusted, aged 16 years and 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 JOLTS data directly.

- **Prices**: taken from the FRED. Gross Domestic Product: Implicit Price Deflator, Index 2009=100, Quarterly, Seasonally Adjusted, GDPDEF

- **Output**: Quarterly real output in the nonfarm 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 presented 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.

Given the large number of parameters to be estimated, we prefer to use 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 (cf. Sims, Stock, and Watson, 1990, for more details on this point).

Estimation procedure

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

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

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 rewrite (17) 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. In more 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 (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.

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 mark-up shocks

This subsection provides an extension to the analysis carried out in Section 5. The residual shock is replaced with a price mark-up 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 substitutability between goods. Thus, an increase in ε leads to a decrease in firms' mark-ups. The distribution of impact responses to a price mark-up shock is presented in Figure 20. 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 mark-up shock implies the same dynamics for output, prices and wages as 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 mark-up shock. Notice that the existence of price mark-up shocks can reconcile the response of participation to technology shocks in the New Keynesian model presented in Section 2 (where it is countercyclical) and in the VAR estimated in Section 5 (where it is mildly procyclical). The VAR result is not necessarily inconsistent with the theoretical model because in that specification technology shocks and price mark-up shocks are not separately identified. The procyclicality in the VAR, in fact, can just reflect the importance of price mark-up shocks. To further investigate this point we use the asymmetric response of participation in order to disentangle price mark-up shocks and technology shocks in the VAR. The restrictions used in this exercise are summarized in Table 5.

Table 5: Sign restrictions

	Demand	Technology	Labor Supply	Wage Bargaining	Price Markup
GDP	+	+	+	+	+
Prices	+	-	-	-	-
Real wages	/	+	-	-	+
Unemployment	-	/	+	-	/
Participation	/	-	+	-	+

Figure 21 presents the variance decomposition for the extended model with price mark-up shocks. Our main result on the absolute and relative importance of the two labor market shocks 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 fairly large share of movements in real wages at all horizons and for around 10 percent of output fluctuations on average over different horizons, thus absorbing some explanatory power from technology shocks. More generally, this exercise can be used to quantify the joint importance of price mark-up and wage bargaining shocks, i.e. the so called "inefficient shocks" in the DSGE literature. Inefficient shocks received a special attention in the literature since they generate large trade-offs between output gap stabilization and inflation stabilization in standard New Keynesian models. Moreover, they are particularly important in the definition of output gap measures. Here we provide a new perspective on the importance of these shocks in the context of a VAR model. According to our results, the two shocks explain on average around 20 percent of output fluctuations, whereas they are more important for the labor market variables and they are relevant for inflation only in the short-run.