



Contents lists available at SciVerse ScienceDirect

Journal of Monetary Economics

journal homepage: www.elsevier.com/locate/jme

Time variation in U.S. wage dynamics

Boris Hofmann^a, Gert Peersman^{b,*}, Roland Straub^c^a Bank for International Settlements, Switzerland^b Department of Financial Economics, Ghent University, W. Wilsonplein 5D, B-9000 Gent, Belgium^c European Central Bank, Germany

ARTICLE INFO

Article history:

Received 17 December 2010

Received in revised form

9 October 2012

Accepted 10 October 2012

Available online 23 October 2012

ABSTRACT

Supply and demand shocks had much stronger long-run effects on nominal wages and prices during the “Great Inflation”. For supply shocks, there is even a sign switch in the nominal wage response. Before and after the “Great Inflation”, nominal wages moved in the same direction as real wages and in the opposite direction of the price level, whereas nominal wages and prices moved in the same direction at longer horizons after the shock in the 1970s. Estimation of a DSGE model shows that these results reflect changes in the degree of wage indexation over time, which was considerably higher during the “Great Inflation”.

© 2012 Elsevier B.V. All rights reserved.

1. Introduction

Time variation in the dynamics of U.S. output and inflation has been extensively explored over the past couple of years. The literature has documented a significant drop in output and inflation volatility since the mid 1980s, a phenomenon referred to as the “Great Moderation”, as well as the rise and fall in the level and persistence of inflation in the wake of the “Great Inflation” of the 1970s (e.g. Blanchard and Simon, 2001; Cogley and Sargent, 2002; McConnell and Perez-Quiros, 2000). Several studies have argued that a shift in the systematic component of monetary policy can explain these phenomena (e.g. Clarida et al., 2000; Galí et al., 2003; Lubik and Schorfheide, 2004), whereas others attribute the changes in macroeconomic fluctuations mainly to a shift in the variance of structural shocks affecting the economy (Stock and Watson, 2002; Primiceri, 2005; Sims and Zha, 2006; Gambetti et al., 2008; Justiniano and Primiceri, 2008).

However, time variation in wage dynamics has not been studied to any great extent in this context, which stands in stark contrast to the important role of wages for macroeconomic outcomes. In modern macroeconomic models, inflation is driven by the dynamics of real marginal costs, which are directly linked to wages.¹ Accordingly, the dynamic adjustment of wages to shocks should matter for macroeconomic dynamics. For instance, if nominal wage growth closely follows the inflation rate because of explicit or implicit wage indexation, inflationary shocks can trigger second-round effects, i.e. mutually reinforcing feedback effects between wages and prices, that can greatly amplify and protract the effects of the shock on inflation. As a consequence, a larger shift in the policy rate is required to bring inflation back to the target. The adjustment of wages is hence crucial for the inflationary consequences of shocks that hit the economy, the costs of disinflation and the volatility of output and prices.

This paper explores the patterns and underlying sources of time variation in U.S. wage dynamics and its interlinkage with time variation in macroeconomic dynamics. The analysis proceeds in two steps. In a first step, an otherwise standard

* Corresponding author. Tel.: +32 9 264 35 14.

E-mail address: gert.peersman@ugent.be (G. Peersman).¹ For instance the New Keynesian Phillips Curve embedded in several DSGE models (e.g. Christiano et al., 2005; Galí and Gertler, 1999; Smets and Wouters, 2007).

time-varying parameters Bayesian structural vector autoregressive (TVP-BVAR) model is estimated including nominal wages in order to assess the time variation in the dynamic effects of a supply and a demand shock. The estimations show that there has been considerable time variation in macroeconomic dynamics, and in particular in nominal wage dynamics. Supply and demand shocks are found to have had much stronger long-run effects on nominal wages and the price level during the “Great Inflation” than in the preceding and subsequent periods. For a supply shock, there is even a sign switch in the long-run co-movement of nominal wages and prices. Specifically, nominal wages moved in the same direction as real wages and in the opposite direction of prices before and after the “Great Inflation”. During the “Great Inflation”, in contrast, nominal wages moved in the same direction as prices and in the opposite direction of real wages at longer horizons after the shock.

Since the TVP-BVAR is silent about the causes of time variation in wage dynamics, in the second step of the analysis, the parameters of a standard DSGE model for specific periods of time are estimated by matching the respective impulse responses for this period from the TVP-BVAR using the Bayesian impulse response matching procedure proposed by [Christiano et al. \(2011\)](#). The estimation of the DSGE model indicates, in line with the existing literature, a less aggressive monetary policy response to inflation and higher price indexation during the “Great Inflation” compared to the earlier and later periods. The results of the matching procedure, however, also reveal that the time variation in wage dynamics uncovered in the VAR analysis reflects considerable variation over time in the degree of wage indexation to past inflation. Wage indexation was very high in the 1970s, in contrast to very low values before and after this period. Specifically, the estimated degree of wage indexation is 0.91 for 1974Q1, compared to 0.30 and 0.17 for respectively 1960Q1 and 2000Q1. This pattern of changes in wage indexation over time is consistent with independent evidence on the use of cost-of-living adjustment (COLA) clauses in major wage bargaining agreements, and turns out to be important for macroeconomic fluctuations. The decline in the degree of wage indexation from 0.91 in 1974Q1 to 0.17 in 2000Q1 implies, for instance, a reduction in the long-run impact of a supply and demand shock on prices by respectively 44% and 39%.

The pattern of time variation in wage indexation supports the notion that the incidence of second-round effects and, as a consequence, the occurrence of wage-price spirals, were pervasive during the “Great Inflation”, but not during the preceding and following periods. This is in line with the widely held perception among policy makers that the incidence of second-round effects of inflationary shocks has fundamentally changed over the past thirty years as a result of the credible establishment of price stability (e.g. [Bernanke, 2006](#)). Indeed, the finding that Fed’s response to inflation and the degree of wage indexation have changed at about the same time suggests that the parameters of a central bank reaction function and the degree of wage and price indexation are two sides of the same coin, i.e. the monetary policy regime. A weakly inflation stabilizing policy rule is conducive to high and volatile inflation. This fosters the use of indexation clauses as protection against inflation uncertainty, which in turn contributes to inflation uncertainty by amplifying the effects of inflationary shocks. On the other hand, a regime of price stability with a more strongly inflation stabilizing policy rule reduces the need for protection against inflation uncertainty, thus mitigating wage and price indexation. A lower degree of indexation in turn reduces the effect of inflationary shocks, thus further contributing to price stability. This reasoning essentially reflects the [Lucas \(1976\)](#) critique that a change in the policy regime could have wider effects on empirical macroeconomic regularities, in this case on the prevalence of indexation practices in wage setting.

This implies that hard-wiring a certain degree of wage indexation in macromodels like the ones of [Christiano et al. \(2005\)](#) or [Smets and Wouters \(2007\)](#) is potentially misleading when changes in the monetary policy regime are analyzed, a point which has also been made by [Benati \(2008\)](#) for price indexation. Also, counterfactual experiments in the context of the “Great Inflation” and “Great Moderation” literature should take the wider implications of changes in the monetary policy regime into account, which has not been the case in several studies concluding that a shift in monetary policy is insufficient or unable to explain the changed macroeconomic dynamics and volatility over time (e.g. [Primiceri, 2005](#); [Sims and Zha, 2006](#); [Canova and Gambetti, 2006](#); [Bilbiie and Straub, in press](#)).

The remainder of the paper is structured as follows. The next section presents the empirical evidence on time variation in U.S. wage dynamics. [Section 3](#) discusses the Bayesian impulse response matching procedure used to estimate the coefficients of a standard DSGE model and presents the estimation results obtained for selected periods of the sample. Finally, [Section 4](#) concludes.

2. Time variation in wage dynamics—stylized facts

To examine time variation in wage dynamics, a VAR(p) model is estimated with time-varying parameters and stochastic volatility in the spirit of [Cogley and Sargent \(2005\)](#) and [Primiceri \(2005\)](#). Within the VAR model, two innovations with a structural economic interpretation are identified at respectively the supply and demand-side of the economy. Together, these innovations consistently explain between 30% and 60% of the long-run forecast error variance of nominal and real wages over the sample period. For output and prices, the contribution to the forecast variance is even higher, reaching values above 70%.² In the next subsections, respectively the reduced form VAR representation, identification strategy and estimation results are discussed.

² Other studies, e.g. [Gambetti et al. \(2008\)](#) and [Benati and Mumtaz \(2007\)](#), also find that similarly identified supply and demand shocks account for the bulk of the volatility in output and prices.

2.1. A Bayesian VAR with time-varying parameters

Consider the following reduced form representation of the VAR:

$$y_t = c_t + B_{1,t}y_{t-1} + \dots + B_{p,t}y_{t-p} + u_t \equiv X_t'\theta_t + u_t \quad (1)$$

where y_t is a vector of observed endogenous variables containing output (seasonally adjusted real GDP), prices (seasonally adjusted GDP deflator), nominal wages (seasonally adjusted hourly compensation in the non-farm business sector) and the interest rate (three-months Treasury bill rate).³ All variables are transformed to non-annualized quarter-on-quarter growth rates by taking the first difference of the natural logarithm, except the interest rate which remains in levels. The overall sample covers the period 1947Q1–2008Q1, but the first 10 years of data are used as a pre-sample to generate the priors for the actual sample period.

The lag length of the VAR is set to $p=2$, which is standard in the literature on time-varying VARs. The time-varying intercepts and lagged coefficients are stacked in θ_t to obtain the state-space representation of the model. The u_t of the observation equation are heteroskedastic disturbance terms with zero mean and a time-varying covariance matrix Ω_t , which can be decomposed in the following way: $\Omega_t = A_t^{-1}H_t(A_t^{-1})'$. A_t is a lower triangular matrix that models the contemporaneous interactions among the endogenous variables and H_t is a diagonal matrix which contains the stochastic volatilities:

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 \end{bmatrix}, \quad H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 \\ 0 & 0 & 0 & h_{4,t} \end{bmatrix} \quad (2)$$

Let α_t be the vector of non-zero and non-one elements of the matrix A_t (stacked by rows) and h_t be the vector containing the diagonal elements of H_t . Following Primiceri (2005), the three driving processes of the system are postulated to evolve as follows:

$$\theta_t = \theta_{t-1} + v_t \quad v_t \sim N(0, Q) \quad (3)$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \quad \zeta_t \sim N(0, S) \quad (4)$$

$$\ln h_{i,t} = \ln h_{i,t-1} + \sigma_i \eta_{i,t} \quad \eta_{i,t} \sim N(0, 1) \quad (5)$$

The time-varying parameters θ_t and α_t are modeled as driftless random walks. The elements of the vector of volatilities $h_t = [h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t}]'$ are assumed to evolve as geometric random walks independent of each other. The error terms of the three transition equations are independent of each other and of the innovations of the observation equation. In addition, a block-diagonal structure for S of the following form is imposed:

$$S \equiv \text{Var}(\zeta_t) = \begin{bmatrix} S_1 & 0_{1 \times 2} & 0_{1 \times 3} \\ 0_{2 \times 1} & S_2 & 0_{2 \times 3} \\ 0_{3 \times 1} & 0_{3 \times 2} & S_3 \end{bmatrix} \quad (6)$$

which implies independence also across the blocks of S with $S_1 \equiv \text{Var}(\zeta_{21,t})$, $S_2 \equiv \text{Var}([\zeta_{31,t}, \zeta_{32,t}]')$, and $S_3 \equiv \text{Var}([\zeta_{41,t}, \zeta_{42,t}, \zeta_{43,t}]')$ so that the covariance states can be estimated equation by equation.

The above model is estimated using Bayesian methods (Markov Chain Monte Carlo algorithm). The priors for the initial states of the regression coefficients, the covariances and the log volatilities are assumed to be normally distributed, independent of each other and independent of the hyperparameters. Specifically, the priors are calibrated on the point estimates of a constant-coefficient VAR estimated over the pre-sample. More details about the prior specifications can be found in the on-line appendix. The posterior distribution is simulated by sequentially drawing from the conditional posterior of four blocks of parameters: the coefficients, the simultaneous relations, the variances and the hyperparameters. To enforce stationarity of the VAR system, an indicator function is included that selects only draws where the roots of the associated VAR polynomial are inside the unit circle (see also Cogley and Sargent, 2005). Further details of the implementation and MCMC algorithm can be found in Primiceri (2005), Benati and Mumtaz (2007) and Baumeister and Peersman (2008). In total 20 000 iterations of the Bayesian Gibbs sampler are performed, but only every 10th draw is kept in order to mitigate the autocorrelation among the draws. After a “burn-in” period of 50 000 iterations, the sequence of draws of the four blocks from their respective conditional posteriors converges to a sample from the joint posterior distribution. The convergence of the chain to the ergodic distribution has been checked by computing the draws’ inefficiency factors, which are also presented in the on-line appendix (see Primiceri, 2005; Benati and Mumtaz, 2007). In total, 2000 simulated values are collected from the Gibbs chain on which the structural analysis is based.

³ The data series were taken from the St. Louis FRED database.

Table 1
Identification of supply and demand shocks.

	Output	Prices	Interest rate	Real wages
Supply shock	≥ 0	≤ 0		≥ 0
Demand shock	≥ 0	≥ 0	≥ 0	

2.2. Identification of supply and demand shocks

Based on the TVP-BVAR, time-variation in the dynamic effects of respectively an aggregate supply and demand shock can be analyzed. For the identification, we follow Peersman and Straub (2009). Specifically, Peersman and Straub (2009) derive a set of sign restrictions that are consistent with a large class of DSGE models and robust for parameter uncertainty to identify both innovations.⁴ The sign restrictions, which are imposed in the first four quarters after the shocks, are summarized in Table 1.

First, a positive supply shock is identified as a shock with a non-negative effect on output and real wages and non-positive effects on prices. These restrictions are sufficient to disentangle the innovations from demand-side and labor supply disturbances. In particular, demand-side shocks are expected to have a positive effect on prices, while expansionary labor supply innovations are typically characterized by a fall in real wages. Notice that the nominal wage response to a supply shock is left unconstrained. The supply shock primarily reflects technology shocks as the most important source of exogenous supply shifts, but it also captures other supply-side shocks such as commodity prices or price mark-up shocks.

Second, a positive (real) demand shock is identified as a shock with non-negative effects on output, prices and the interest rate. The restriction on the interest rate should differentiate the shock from nominal disturbances such as monetary policy shocks. Examples of such (real) demand shocks are government spending, time-impatience or investment shocks.

2.3. Estimation results

The main results are summarized in Figs. 1–4. The figures plot the time-varying contemporaneous impact and long-run effect (i.e. the effect 28 quarters after the shock) of a one standard deviation supply shock and demand shock on respectively the level of nominal wages, prices, output and real wages. The figures show the median, as well as the 16th and 84th percentiles of the posterior distributions of the impulse responses.⁵ Full results for all variables at all horizons are shown in the (three-dimensional) charts in the on-line appendix (Figs. A2 and A3).

The figures reveal that there is considerable time variation in the dynamic effects of the shocks. The most striking time-variation is the long-run impact of both shocks on nominal wages and the price level (Figs. 1 and 2). Specifically, positive supply and demand shocks have respectively a much stronger negative and positive long-run effect on nominal wages and prices between the end of the 1960s and the early 1980s, i.e. during the “Great Inflation” period, compared to the preceding and subsequent periods. Remarkably, in the case of supply shocks, there is even a sign switch in the long-run response of the nominal wage, from positive to negative just before 1970 and then back to positive just after 1980. At the same time, there is basically no time variation in the immediate response of nominal wages to supply shocks, which has always been positive and even of a similar magnitude. Only after a few quarters, there is a sign switch in the nominal wage reaction in the 1970s.

⁴ Peersman and Straub (2009) propose this identification strategy with sign restrictions as an alternative to Galí’s (1999) long-run restrictions to estimate the impact of technology shocks on hours worked and employment. Galí’s identification strategy, however, cannot be implemented in our time-varying SVAR. To keep the number of variables manageable, we do not have hours worked or labor productivity as one of the variables in the model. The approach of Peersman and Straub (2009) does instead not need these variables for identification purposes. Imposing long-run neutrality of non-technological disturbances in a model where the underlying structure and dynamics change over time is also something difficult to implement without making additional assumptions. See also Dedola and Neri (2007) and Peersman (2005) for a similar sign restrictions approach.

⁵ To compute the impulse response functions, a Monte Carlo integration procedure is used, which accounts for all the potential sources of uncertainty deriving from the additive innovations, variations in lagged coefficients and changes in the contemporaneous relations among the variables. More precisely, the generalized impulse responses are computed as the difference between two conditional expectations with and without the exogenous shock:

$$IRF_{t+k} = E[y_{t+k}|e_t, \omega_t] - E[y_{t+k}|\omega_t]$$

where y_{t+k} contains the forecasts of the endogenous variables at horizon k , ω_t represents the current information set and e_t is the current disturbance term. At each point in time, the information set we condition upon contains the actual values of the lagged endogenous variables and a random draw of the model parameters and hyperparameters. In particular, in order to calculate the conditional expectations we randomly draw from the Gibbs sampler one possible state of the economy at time t represented by the time-varying lagged coefficients and the elements of the variance-covariance matrix. Based on this draw, we employ the transition laws and stochastically simulate the future paths of the coefficient vector and the components of the variance-covariance matrix. To obtain the time-varying structural impact matrix, the QR decomposition procedure proposed by Rubio-Ramírez et al. (2010) is implemented. The figures are based on 1000 draws for each quarter over the sample period. The impulse response function of the real wage for each draw is obtained via the response of the nominal wage rate and the GDP deflator.

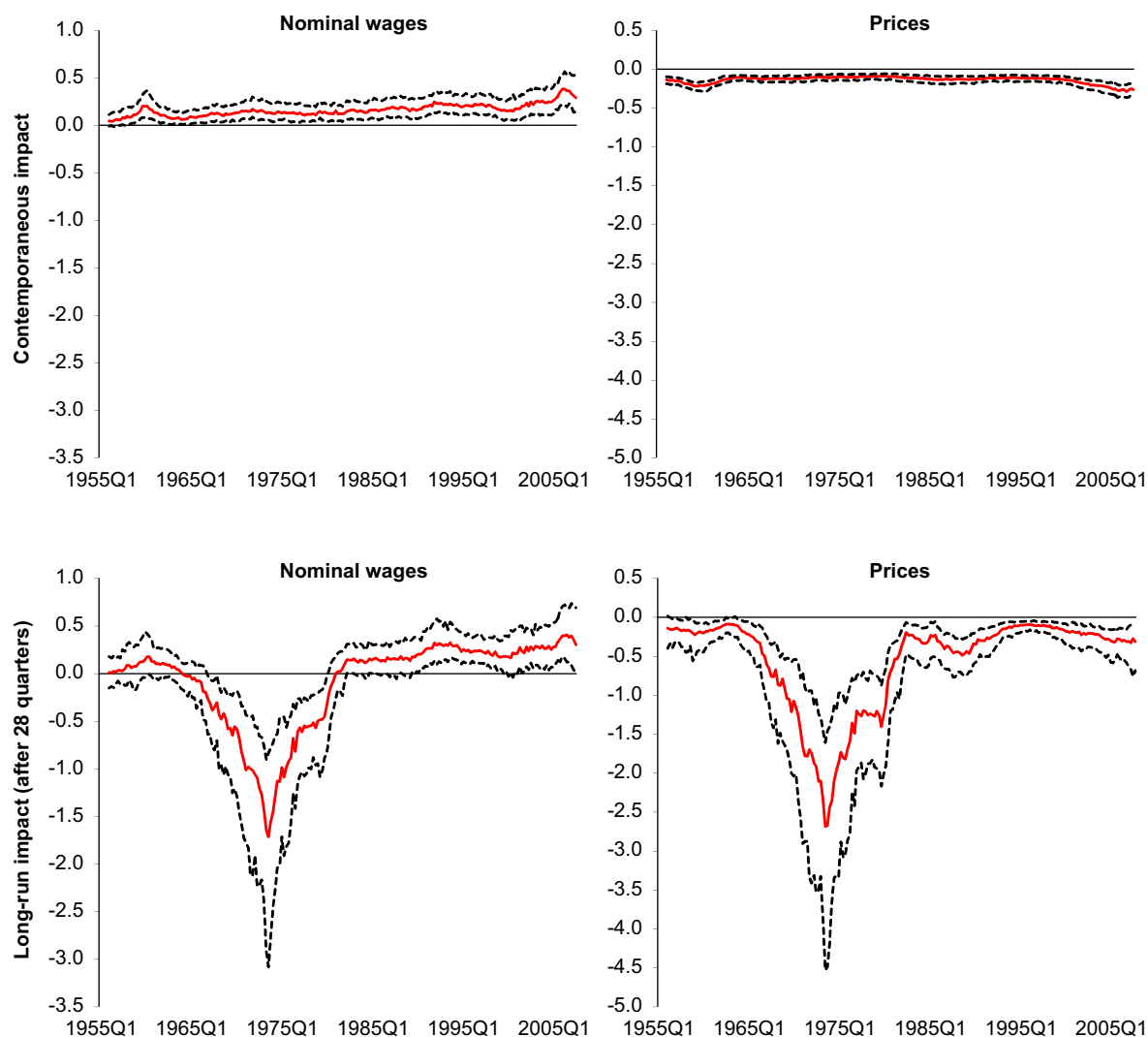


Fig. 1. Contemporaneous and long-run impact of supply shock on nominal wages and prices over time. *Note:* Figures are the medians of the posterior distribution for each quarter in the sample period, together with 16th and 84th percentiles. Estimations done with time-varying parameters Bayesian VAR; impact respectively 0 (contemporaneous) and 28 (long-run) quarters after the shock.

The sign switch in the response of nominal wages to a supply shock at the start and at the end of the “Great Inflation” is a new stylized fact which has not been documented before. As a matter of fact, the few studies that do analyze the impact of supply (technology) shocks on wages using SVARs assume constant parameters over the whole sample period (e.g. Basu et al., 2006; Liu and Phaneuf, 2007) conclude that there is only a very weak negative or insignificant response of nominal wages accompanying a significant rise in real wages. The present analysis suggests that this result is misleading as it ignores considerable time variation in the reaction pattern of nominal wages. More generally, from the perspective of our results, empirical studies of changes in macroeconomic dynamics only distinguishing between the period after the disinflation of the early 1980s, i.e. the so-called Volcker–Greenspan period, and preceding period, i.e. the so-called pre-Volcker period, miss a change in the macroeconomic regime. The results indicate that the pre-Volcker period actually covers two different regimes with fundamentally different dynamics.⁶

Although the exact magnitude of the shocks cannot be pinned down,⁷ the smaller contemporaneous impact of demand shocks and the smaller immediate and long-run (permanent) effects of supply shocks on economic activity since the early

⁶ For instance, Galí et al. (2003) detect a much stronger impact of a technology shock on inflation in the pre-Volcker period (1954Q1–1979Q2) relative to the Volcker–Greenspan era (1982Q3–1998Q3). Our results, however, suggest that their pre-Volcker–Greenspan era covers two regimes with significantly different dynamics.

⁷ This is a well-known problem when VAR results are compared across different samples (see Baumeister and Peersman, 2008 for a detailed discussion of this problem). Only the impact of an “average” shock on a number of variables can be measured. Consequently, it is not possible to know

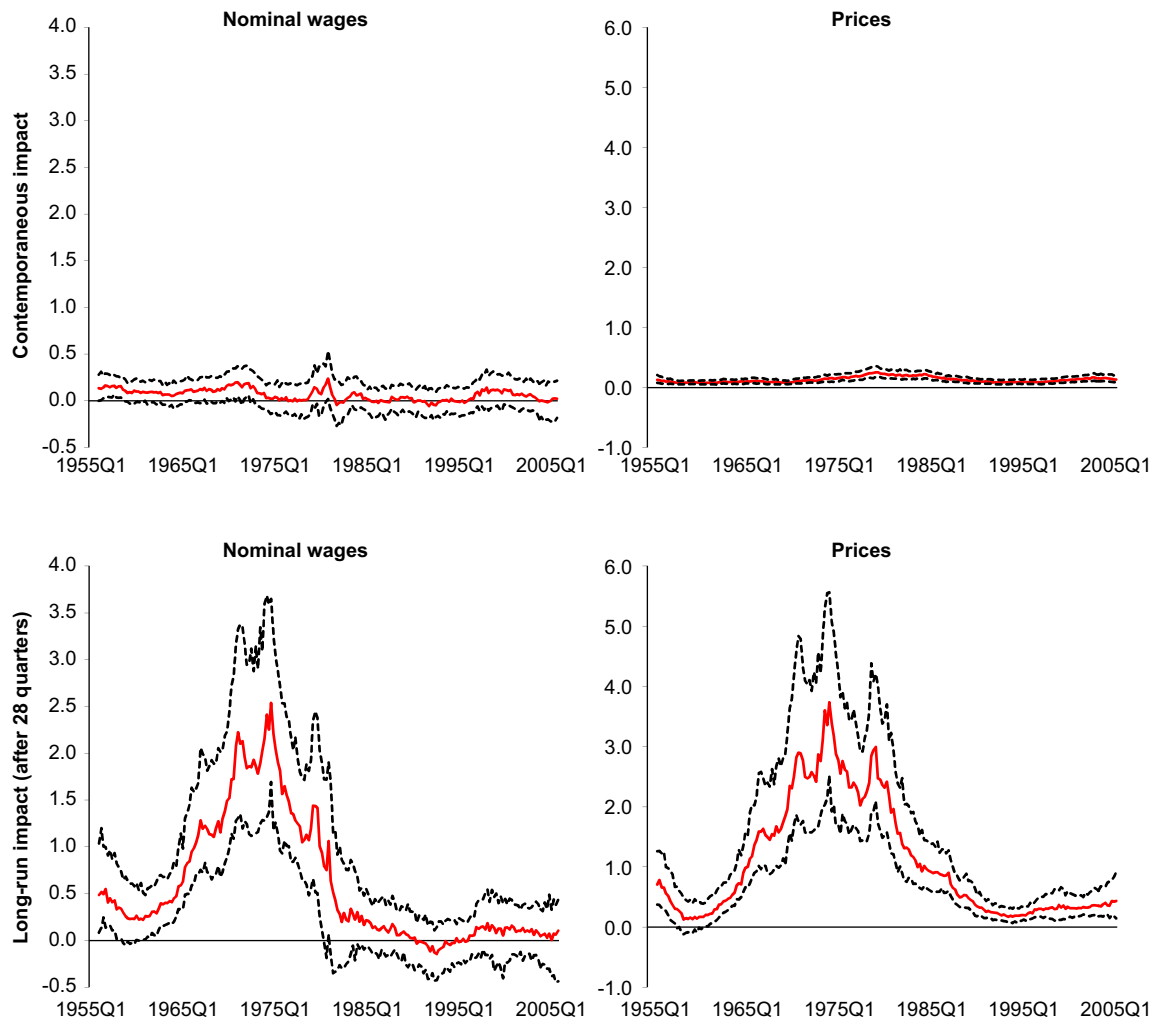


Fig. 2. Contemporaneous and long-run impact of demand shock on nominal wages and prices over time. *Note:* Figures are the medians of the posterior distribution for each quarter in the sample period, together with 16th and 84th percentiles. Estimations done with time-varying parameters Bayesian VAR; impact respectively 0 (contemporaneous) and 28 (long-run) quarters after the shock.

1980s (Figs. 3 and 4),⁸ appear consistent with the so-called “good luck” hypothesis of the “Great Moderation”, i.e. the notion that the lower macroeconomic volatility over this period is at least in part due to systematically smaller shocks. However, it is implausible that only changes in the size of shocks are driving the pattern of the responses of prices and nominal wages over time. If this were the case, then we should see the same pattern of time variation in the impulse responses of the other variables, which is not the case. For instance, there is no evidence of a reduced effect of supply shocks on real wages, a variable which is also expected to be closely related to productivity changes. The short-run effect is even found to have slightly increased over time, while the long-run effect has remained at the elevated levels reached in the early 1970s.⁹ The time variation of the output effects is also much more subdued in terms of magnitude than the time variation of the impact on nominal wages and prices. And, most importantly, a different size of the underlying shocks over time cannot explain why the contemporaneous impact of supply shocks on nominal wages has always been positive (and

(footnote continued)

exactly whether the magnitude of an average shock has changed or the reaction of the economy (economic structure) to this shock, unless an arbitrary normalization on one of the variables is done (e.g. Gambetti et al., 2008 normalize demand shocks on output and supply shocks on prices).

⁸ Given the estimated long-run neutrality on output (with the exception of two quarters within the sample), the impact of aggregate demand shocks on economic activity is best captured by its immediate effect. In particular, the contemporaneous impact is always very close to the maximum effect of the shock on output.

⁹ This result is in line with recent micro-evidence reported by Davis and Kahn (2008), who document that the “Great Moderation” was not associated with a reduction in household income volatility. Interesting is also the negative long-run response of real wages to a demand shock, in particular during the 1970s. By simulating a standard DSGE model, Peersman and Straub (2009) show that the sign of the effects of demand-side shocks on real wages depends on the combination of the parameter values of the model. A more detailed analysis of the source is out of the scope of this paper.

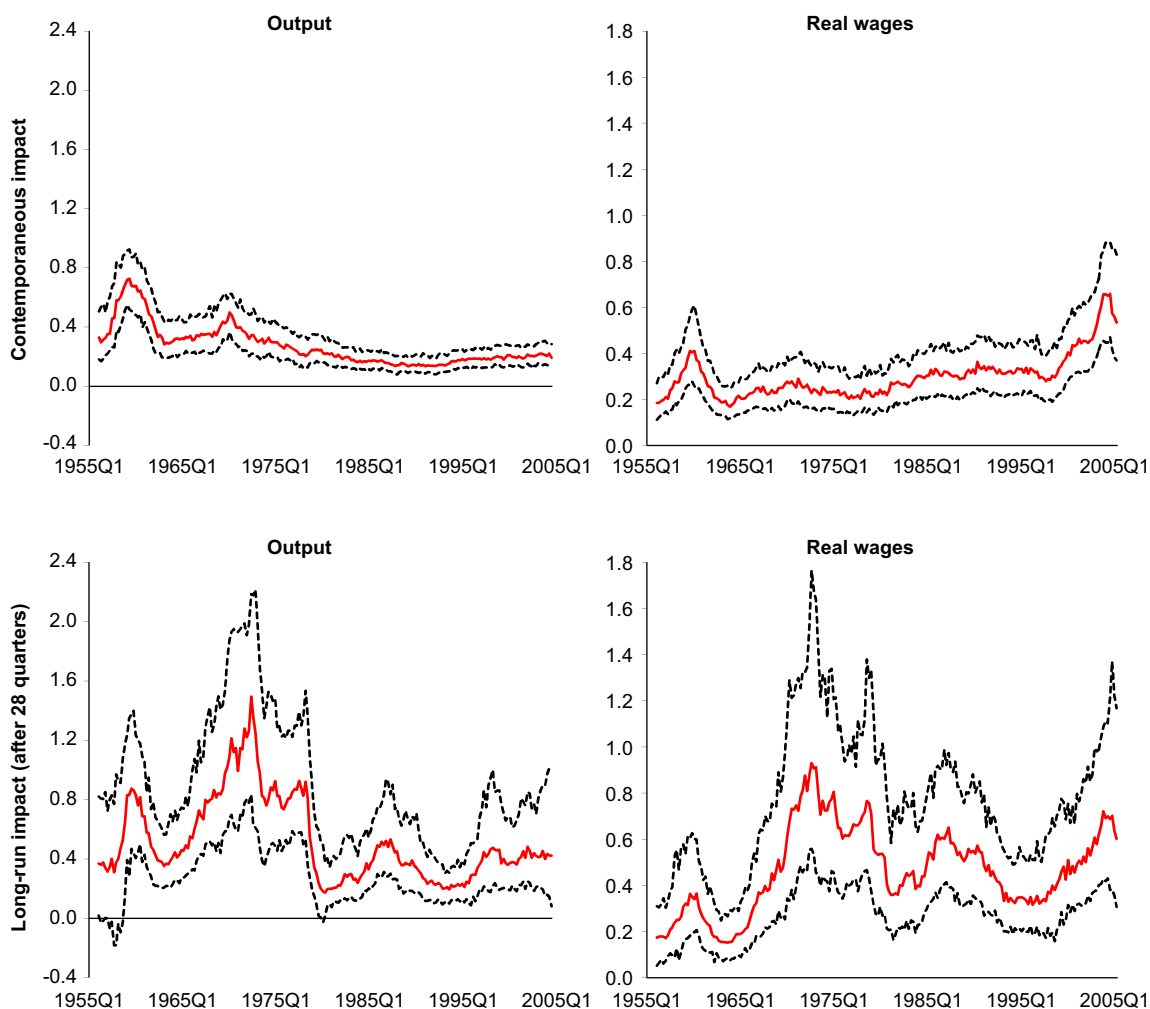


Fig. 3. Contemporaneous and long-run impact of supply shock on output and real wages over time. *Note:* Figures are the medians of the posterior distribution for each quarter in the sample period, together with 16th and 84th percentiles. Estimations done with time-varying parameters Bayesian VAR; impact respectively 0 (contemporaneous) and 28 (long-run) quarters after the shock.

of a similar magnitude), whereas the long-run effects became negative at the start of the “Great Inflation” and changed back to positive at the end of this episode in the early 1980s. The sign switches in the reaction of nominal wages to supply shocks clearly points to structural changes in the economy. In the next section, this is examined more carefully.

3. Explaining the time-variation in wage dynamics

In order to assess the causes of the time variation in wage dynamics in a more structural and comprehensive manner, the parameters of a standard DSGE model for specific periods are estimated by matching the respective impulse responses for this period from the TVP-VAR using a Bayesian impulse response matching procedure in the spirit of [Christiano et al. \(2011\)](#). This should allow to better disentangle the underlying reasons for the time variation, which was not possible within the confines of the VAR analysis.

In the impulse response matching exercise, the VAR supply shock impulse responses are matched with the DSGE model impulse responses to a permanent technology shock and the VAR demand shock impulse responses with the DSGE model impulse responses to a government spending shock. Matching the supply shock with a technology shock is consistent with the notion that technology shocks are the most important source of exogenous supply shifts. While the finding that there is a sign switch in the wage response to a supply shock is clearly the most interesting result from the VAR analysis and hence also the focus of the impulse-response matching exercise, the VAR results for the demand shock are also exploited in order to strengthen identification of the model coefficients (relative to a procedure solely based on the matching of the supply and technology shock). To this end, the impulse responses of the demand shock are matched with the DSGE impulse responses of a government spending shock. This involves the implicit assumption that other potentially important

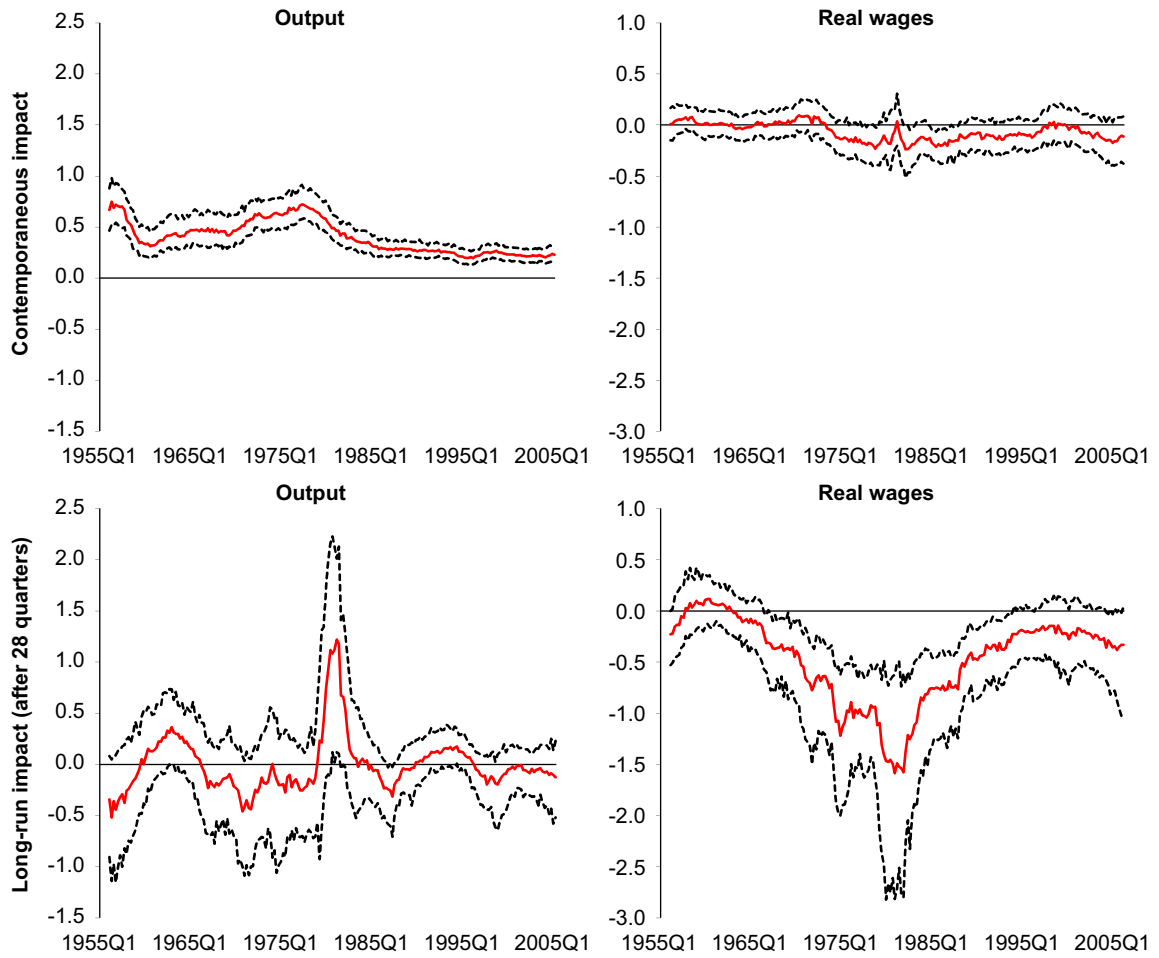


Fig. 4. Contemporaneous and long-run impact of demand shock on output and real wages over time. *Note:* Figures are the medians of the posterior distribution for each quarter in the sample period, together with 16th and 84th percentiles. Estimations done with time-varying parameters Bayesian VAR; impact respectively 0 (contemporaneous) and 28 (long-run) quarters after the shock.

demand shocks, such as preference shocks, have effects on the observable variables that are similar to those of a government spending shock.

3.1. The model

We use a standard DSGE model with Calvo sticky prices and wages, price and wage indexation, habit formation, and a conventional Taylor rule. The model can be considered as a simplified version of Smets and Wouters (2007) or Christiano et al. (2005). This section presents the log-linearized equations of the model. Details of the derivation, including the agent's objective functions and constraints, can be found in the on-line appendix.

The DSGE model economy is subject to a (permanent) technology and government spending shock. To induce stationarity, the real variables in the model are divided by the level of the permanent productivity shock A_t . As a result, the transformed variables output, consumption, government spending and real wages are $\tilde{Y}_t = Y_t/A_t$, $\tilde{C}_t = C_t/A_t$, $\tilde{G}_t = G_t/A_t$ and $\tilde{W}_t = W_t/P_t A_t$. Furthermore, log-deviations of a stationary variable \tilde{X}_t from its steady-state value are labeled by $\tilde{x}_t = \log(\tilde{X}_t/\bar{X})$. In what follows, the stationary equilibrium of the log-linearized model that is used for the estimations is described.

First, price inflation dynamics are explained by a Phillips Curve augmented with price indexation:

$$\pi_t = \frac{\beta}{(1+\beta\gamma_p)} E_t \pi_{t+1} + \frac{\gamma_p}{(1+\beta\gamma_p)} \pi_{t-1} + \frac{(1-\beta\theta_p)(1-\theta_p)}{(1+\beta\gamma_p)\theta_p} \tilde{w}_t \quad (7)$$

whereby π_t is the price inflation rate, E_t is the expectations operator at time t , γ_p is price indexation, β is the time preference rate and θ_p measures the degree of nominal price rigidity in the Calvo pricing model. Correspondingly, wage

inflation π_t^w is modeled by the following equation:

$$\pi_t^w = \beta E_t \pi_{t+1}^w - \gamma_w \beta \pi_t + \gamma_w \beta \pi_{t-1} + \frac{1}{(1+\beta)} \frac{(1-\beta\theta_w)(1-\theta_w)}{\left(\theta_w \left(1 + \frac{1+\lambda_w \gamma}{\lambda_w \zeta}\right)\right)} \begin{pmatrix} \frac{1}{1-b} \tilde{c}_t + \zeta n_t \\ -\tilde{w}_t - \frac{b}{1-b} (\tilde{c}_{t-1} - \Delta a_t) \end{pmatrix} \quad (8)$$

whereby γ_w is the degree of wage indexation, λ_w is the degree of monopolistic competition in the labor market, ζ is the labor supply elasticity, θ_w measures the degree of nominal rigidity in a Calvo pricing model, n_t is hours worked, and Δa_t is the first difference of the stochastic productivity process a_t . Real wage dynamics are described by the following equation:

$$\tilde{w}_t = \tilde{w}_{t-1} + \pi_{w,t} - \pi_t - \Delta a_t \quad (9)$$

Consumption dynamics is modeled via the following standard Euler equation:

$$r_t - E_t \pi_{t+1} = \frac{1}{1-b} (E_t \tilde{c}_{t+1} - (1+b)\tilde{c}_t + b\tilde{c}_{t-1} - b\Delta a_t) \quad (10)$$

where r_t is the nominal interest rate, and b is the degree of habit persistence. The aggregate resource constraint of the economy is described by

$$\tilde{y}_t = \frac{C}{Y} \tilde{c}_t + \frac{G}{Y} \tilde{g}_t \quad (11)$$

where G/Y represent the share of government spending in terms of output in the stationary steady state. Aggregate supply is represented by the following linear production function:

$$\tilde{y}_t = n_t \quad (12)$$

Monetary policy follows a Taylor rule, with the interest rate reacting to lagged interest rates, inflation, output gap and the change in the output gap:

$$r_t = \rho^r r_{t-1} + (1-\rho^r)(\phi^y \tilde{y}_t + \phi^\pi \pi_t) + \phi^{\Delta y} \Delta \tilde{y}_t \quad (13)$$

where ρ^r is a parameter determining the degree of interest rate smoothing, while $\phi^{\Delta y}$, ϕ^y and ϕ^π represent the elasticity of the interest rate to the change in the output gap, output gap and inflation respectively.

The exogenous process for the technology shock is defined as $a_t = \rho^a a_{t-1} + \eta_t^a$ with $\rho^a = 1$, implying a random walk productivity shock that induces permanent effects, which is in line with the VAR estimations reported above. The exogenous shock process for government spending follows an AR(1) process in its log-linearized form $\tilde{g}_t = \rho^g \tilde{g}_{t-1} + \eta_t^g$. Note that it is assumed that government spending grows along the balanced growth path ensuring in the long run a stable share of government spending to output despite permanent technology shocks. For simplicity, it is also assumed that the government budget is always in balance, financed by a lump-sum tax T_t , i.e. $G_t = T_t$ holds for each period in time.

3.2. Methodology

The DSGE model of Section 3.1 is estimated with Bayesian minimum distance techniques in the spirit of Christiano et al. (2011). We focus on the impulse response functions of 1960Q1, 1974Q1 and 2000Q1, which represent the three regimes of wage and price dynamics that were uncovered in the VAR analysis: the period before the start of the “Great Inflation”, the “Great Inflation” and the Volcker–Greenspan era.¹⁰ The VAR impulse response functions were recalculated under the assumption that the parameters do not change over the horizon of the impulse responses. This is necessary as we want to estimate the structural parameters of the model associated with the VAR impulse responses in a specific point in time without any influence of future time variation in the structure of the economy.

The main difference to Christiano et al. (2011) is that the impulse response functions that have to be matched are generated with a Bayesian VAR, while the shocks are identified with sign restrictions. Accordingly, there is no point estimate around which the minimum distance method can be centered. As an alternative, in a first step, the posterior mode of the structural parameters for each of the 1000 impulse response functions that fulfill the selected sign restrictions in the VAR is estimated. In a second step, the corresponding distribution of the posterior modes for each of the structural parameters is calculated.¹¹ In what follows, we summarize the Bayesian minimum distance estimator, closely following the description in Christiano et al. (2011).

More precisely, the estimated impulse response functions are first stacked into a vector $\hat{\psi}$, which has a dimension of 28 (horizon of responses) times 2 (number of shocks) times 4 (number of variables) for each of the draws. When the number of observations, T , is large, standard asymptotic theory shows that:

$$\sqrt{T}(\hat{\psi} - \psi(\theta_0)) \overset{d}{\rightarrow} N(0, W(\theta_0, \zeta_0)) \quad (14)$$

¹⁰ The results are however robust to the choice of different periods from these three regimes.

¹¹ So in what follows, the median of the distribution always refers to the median of the distribution of the posterior modes. Alternatively, one could also calculate the marginal posterior distribution of the selected parameters for each of the 1000 draws using Markov chains. Note, however, that this approach cannot be accomplished in an acceptable amount of time.

where θ_0 represents the true value of the parameters which are estimated, while ζ_0 denotes the true values of the parameters of the shocks that are in the model. As a result, the asymptotic distribution of $\hat{\psi}$ can be written in the following form:

$$\hat{\psi}^a \sim N(\psi(\theta_0), V(\theta_0, \zeta_0, T)) \quad (15)$$

$$V(\theta_0, \zeta_0, T) \equiv \frac{W(\theta_0, \zeta_0)}{T} \quad (16)$$

In a next step, $\hat{\psi}$ is treated as data and the value of θ is chosen to minimize the distance between $\psi(\theta)$ and $\hat{\psi}$. Thereby, the approximate likelihood of the data, $\hat{\psi}$, is defined as function of θ :

$$f(\hat{\psi}|\theta) = \left(\frac{1}{2\pi}\right)^{N/2} |V(\theta_0, \zeta_0, T)|^{-1/2} \times \exp\left[-\frac{1}{2}(\hat{\psi} - \psi(\theta_0))' V(\theta_0, \zeta_0, T)^{-1} (\hat{\psi} - \psi(\theta_0))\right] \quad (17)$$

In Eq. (17), N denotes the number of elements in $\hat{\psi}$ and $V(\theta_0, \zeta_0, T)$ is treated as a fixed value. In particular, the weight matrix depends on the second moments of the conditional impulse response function in each period, i.e. the wider the posterior distribution of the empirical impulse responses at a point in time, the less weight is given to the corresponding observation. As the function f is defined as the likelihood of $\hat{\psi}$, it follows that the Bayesian posterior of θ conditional on $\hat{\psi}$ and $V(\theta_0, \zeta_0, T)$ can be written as

$$f(\theta|\hat{\psi}) = \frac{f(\hat{\psi}|\theta)p(\theta)}{f(\hat{\psi})} \quad (18)$$

where $p(\theta)$ denotes the priors on θ and $f(\hat{\psi})$ is the marginal density of $\hat{\psi}$. The mode of the posterior distribution of θ can be computed by maximizing the value of the numerator in Eq. (18).

3.3. Results

Table 2 reports the priors of the DSGE model parameters that are used to match the VAR impulse response functions. The density with admissible parameter range are reported, as well as the mean and the standard deviation. The priors have been specified in a standard way, following previous studies estimating DSGE model parameters using Bayesian techniques.¹² In line with the empirical literature, some of the structural parameters are set to a fixed value from the start: the discount factor $\beta = 0.99$; the inverse labor supply elasticity $\zeta = 2$; and the degree of monopolistic competition in respectively the goods and labor market $\lambda_p = \lambda_w = 10$. These parameter values are consistent with calibrations in previous studies.¹³

The 68% coverage percentiles of the impulse responses of the DSGE model obtained from the matching procedure, together with the same percentiles of the VAR impulse responses, are shown in Fig. 5. As can be seen from the charts, the DSGE is able to match the VAR impulse responses fairly well. The only exception is the interest rate response to the demand shock in the 1960s and the 2000s, where the model impulse responses are more subdued than the VAR impulse responses. Importantly, the model can reproduce the magnitudes and the sign switch of the long-run wage response over the three regimes to the supply shock. It can also match the sign switch of the nominal wage response to the supply shock in the 1970s from positive on impact to negative over longer horizons.

The distributions of the estimated posterior mode of the model parameters are summarized in Table 2 by reporting the median and the 16th and 84th percentiles. For the price and wage stickiness parameters there is no indication of a material change over time. The percentile ranges of the estimates are consistent with estimates of these two parameters reported in previous studies (e.g. Christiano et al., 2005; Smets and Wouters, 2007). The estimates, however, reveal considerable time variation in a number of other structural parameters of the model. First, the estimated standard deviation of the shocks support the hypothesis that “good luck” in the form of smaller exogenous shocks contributed to the “Great Moderation”. The median estimates of the standard deviations of the supply and the demand shock are both notably smaller in 2000 than in the two earlier periods. Second, there is a hump-shaped pattern over the three periods for the habit persistence parameter, with a median estimate of around 0.35 for the periods 1960 and 2000 and of 0.71 for 1974. The distributions, however, are rather wide and overlap for the 1970 and 2000 periods.

Third, the parameters of the monetary policy rule display a pattern over time that is consistent with the evidence on the evolution of the conduct of U.S. monetary policy over time. In particular, the inflation reaction coefficient displays a U-shaped pattern across the three periods. The median estimate is around 1.55 and 1.35 for 1960 and 2000 respectively, and 1.11 for 1974. There is essentially no variation in the interest rate reaction to the level of the output gap, but the

¹² See e.g. Smets and Wouters (2007) and Christiano et al. (2011). Like these studies, we impose an inflation reaction parameter which is larger than 1 thus neglecting the possibility of indeterminacy. Lubik and Schorfheide (2004) and Justiniano and Primiceri (2008) estimate DSGE models allowing for indeterminacy in the 1970s.

¹³ Robustness checks showed that the main results are not materially affected by choosing different parameter values within a reasonable range for the labor supply and the wage and price mark-up parameters.

Table 2
Priors and posterior estimates of DSGE model parameters.

Parameter		Prior		Posterior		
		Density [bounds]	Mean (Std. dev.)	1960 Median [16%,84%]	1974 Median [16%,84%]	2000 Median [16%,84%]
γ_p	Price indexation	Beta	0.5 (0.2)	0.15 [0.11,0.19]	0.80 [0.58,0.93]	0.17 [0.12,0.21]
γ_w	Wage indexation	Beta	0.5 (0.2)	0.30 [0.21,0.67]	0.91 [0.74,0.96]	0.17 [0.11,0.25]
θ_p	Price stickiness	Beta	0.75 (0.05)	0.81 [0.76,0.85]	0.84 [0.81,0.87]	0.78 [0.70,0.84]
θ_w	Wage stickiness	Beta	0.75 (0.05)	0.60 [0.46,0.85]	0.64 [0.54,0.73]	0.54 [0.43,0.69]
b	Consumption habit	Beta	0.5 (0.1)	0.33 [0.21,0.40]	0.71 [0.51,0.96]	0.37 [0.18,0.57]
ρ^r	Taylor rule smoothing	Beta	0.7 (0.1)	0.76 [0.68,0.82]	0.69 [0.58,0.87]	0.78 [0.70,0.88]
ϕ^π	Taylor rule inflation	Gamma	1.5 (0.2)	1.55 [1.34,1.74]	1.11 [1.07,1.18]	1.35 [1.24,1.49]
ϕ^y	Taylor rule output	Gamma	0.5 (0.2)	0.10 [0.07,0.16]	0.11 [0.06,0.29]	0.10 [0.07,0.15]
$\phi^{\Delta y}$	Taylor rule Δ output	Gamma	0.2 (0.1)	0.30 [0.21,0.40]	0.50 [0.27,0.84]	0.39 [0.27,0.59]
σ_a	Std. dev. Tech. shock	Inv.Gamma	1.0 (0.5)	0.60 [0.46,0.85]	1.02 [0.71,1.69]	0.31 [0.25,0.42]
σ_g	Std. dev. Dem. shock	Inv.Gamma	1.0 (0.5)	4.75 [3.41,7.92]	4.73 [3.94,5.95]	3.25 [2.30,6.22]
ρ^g	Autocorr. Dem. shock	Beta	0.9 (0.1)	0.87 [0.83,0.92]	0.89 [0.86,0.93]	0.91 [0.87,0.95]

reaction to the change in the output gap is estimated to have been somewhat higher in 1974 than in 1960 and 2000, although the percentile ranges for this parameter are rather wide. The very low interest rate response to inflation estimated for 1974 corroborates very well with the “bad monetary policy” hypothesis of the “Great Inflation” that has been brought forward by Judd and Rudebusch (1999), Clarida et al. (2000), Cogley and Sargent (2002, 2005) among others.¹⁴ The time variation in the price indexation parameter is also in line with earlier studies documenting a rise and decline of U.S. inflation persistence associated with the onset and conquest of the “Great Inflation” (e.g. Cogley and Sargent, 2002, 2005; Kang et al., 2009). In particular, the median of the estimated price indexation coefficient is around 0.15 in 1960 and 2000, while it is 0.8 for 1974.

More importantly in the context of the present study, there is also considerable time variation in the wage indexation parameter. The median estimate of this coefficient is 0.91 for 1974 and respectively 0.3 and 0.17 for 1960 and 2000. While the parameter for 1960s has a wider distribution, the percentile ranges for 1974 and 2000 are relatively tight. The relevance of wage indexation for macroeconomic dynamics over time is also considerable. For instance, when the DSGE model is estimated with the posterior median parameter values of 1974, the impact of a supply shock on prices after 5 years is 44% lower when the wage indexation parameter is replaced by its 2000 posterior median value only. As a benchmark, if the same exercise is done for the monetary policy rule and price indexation parameters, there is a reduction of respectively 31% and 23%. Similarly, when the effects of a demand shock are simulated, the impact on prices is 39% less when the wage indexation parameter is substituted, compared to 19% and 37% for price indexation and the systematic part of the policy rule.

To summarize, the estimates of the DSGE model parameters obtained from the Bayesian impulse response matching procedure suggest that the patterns of time variation in the VAR impulse responses primarily reflect a high degree of price and wage indexation in conjunction with a weak reaction of monetary policy to inflation during the “Great Inflation”, and low indexation together with aggressive inflation stabilization of monetary policy before and after this period. While the findings in the time-variation of the price indexation parameters and the inflation reaction coefficient in the monetary policy rule confirm results of previous studies, the strong evidence of a change in wage indexation over time, in particular its role for time variation in macroeconomic dynamics, is entirely a new result.

¹⁴ Orphanides (2003) suggests however that the evidence of fundamental differences in the conduct of monetary policy during the Great Inflation compared to the subsequent era of price stability is considerably mitigated when real-time data are used for the analysis of policy rules. Bilbiie and Straub (in press), on the other hand, suggest that the low inflation responsiveness of monetary policy in the 1970s can be rationalized by limited asset market participation during this period.

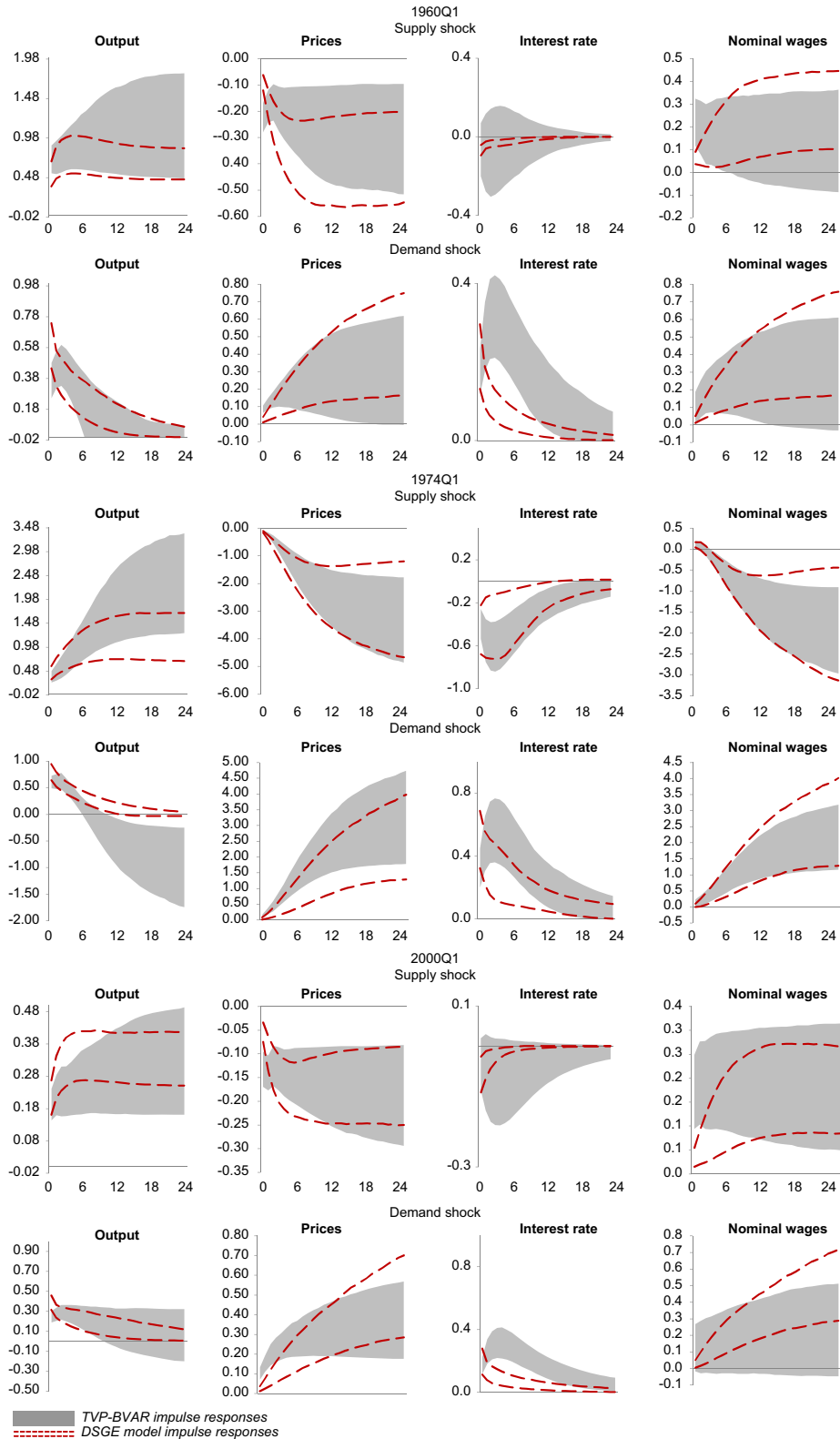


Fig. 5. VAR and DSGE-model impulse responses for 1960Q1, 1974Q1 and 2000Q1. Note: 16th and 84th percentiles of the posterior distributions, quarterly horizon.

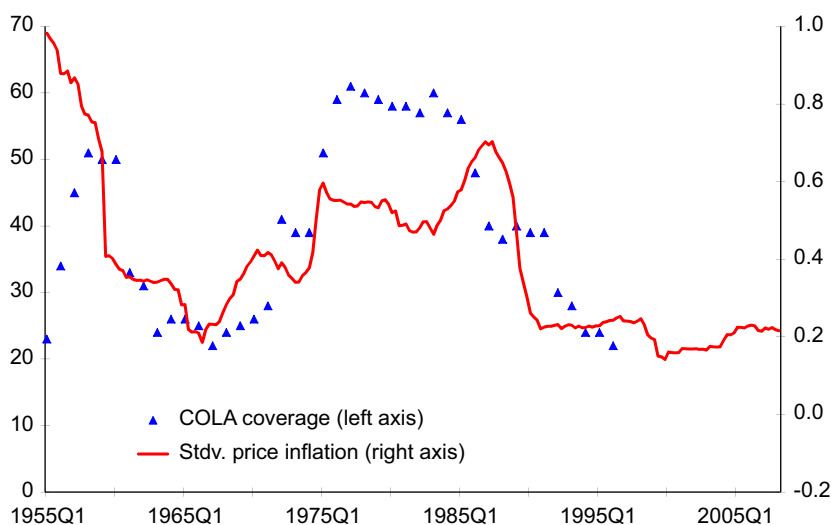


Fig. 6. COLA coverage and inflation variability. *Note:* COLA=cost-of-living adjustment clauses included in major collective bargaining agreements (i.e. contracts covering more than 1000 workers). Figures refer to end of preceding year. *Source:* Hendricks and Kahn (1985), Weiner (1986) and Bureau of Labor Statistics. The observation for 1956 is interpolated, and the series has been discontinued in 1996. Standard deviation of price inflation is calculated as an 8-year moving window.

3.4. Link with institutional evidence

The pattern of time-variation in the wage indexation parameter described above is consistent with institutional evidence on wage indexation practises. Specifically, Fig. 6 shows the coverage of private sector workers by cost-of-living adjustment (COLA) clauses.¹⁵ The chart reveals that, from the late 1960s onwards, COLA coverage steadily increased to levels around 60% in the mid 1980s, after which there was again a decline towards 20% in the mid 1990s, when the reporting of COLA coverage has been discontinued. As a matter of fact, studies by Holland (1986, 1995) and Ragan and Bratsberg (2000) find a significant positive impact of inflation and inflation uncertainty on the prevalence of such COLA clauses included in major collective wage bargaining agreements.¹⁶ Interestingly, our results suggest that increased wage indexation itself in turn leads to additional inflation variability *via* second-round effects, thus further strengthening the incentive to include cost-of-living adjustments in collective bargaining agreements.

4. Conclusions

There are two new results on the dynamic adjustment of the U.S. economy to shocks and its underlying causes. First, there is considerable time variation in U.S. macroeconomic dynamics and in particular in U.S. nominal wage dynamics following supply and demand shocks over the post-WWII period. Specifically, evidence from a time-varying structural VAR shows that positive supply and demand shocks have respectively a much stronger negative and positive long-run effect on nominal wages and prices between the end of the 1960s and the early 1980s compared to the preceding and subsequent periods. Strikingly, in the case of supply shocks, there is even a sign switch in the long-run response of the nominal wage, from positive to negative just before 1970 and then back to positive just after 1980. Second, estimation of a simple DSGE model reveals that these results are driven in particular by time-variation in wage indexation, i.e. a high degree of wage indexation during the “Great Inflation” and low indexation in the preceding and subsequent low inflation periods. This pattern of changes in wage indexation over time is consistent with independent evidence on the use of cost-of-living adjustment (COLA) clauses in major wage bargaining agreements. In line with previous studies, the DSGE estimation further reveals a weak reaction of monetary policy to inflation and high price indexation during the “Great Inflation”, and more aggressive inflation stabilization of monetary policy and low price indexation before and after this period.

The evidence presented in this paper suggests that, during the “Great Inflation”, supply and demand shocks have triggered second-round effects, in particular *via* high wage indexation, which amplified the ultimate effects on prices and hence increased inflation variability. This mechanism can also explain the sign switch in the long-run nominal wage

¹⁵ COLA coverage obviously only measures explicit wage indexation in major wage agreements for unionized workers and does therefore not capture explicit wage indexation in other wage agreements or implicit wage indexation. However, Holland (1988) shows that COLA coverage is positively related to the responsiveness of union, non-union and economy-wide wage aggregates to price level shocks and suggests, based on this finding, that COLA coverage is a suitable proxy for the overall prevalence of explicit and implicit wage indexation in the U.S. economy.

¹⁶ Ehrenberg et al. (1984) show in an efficient contract model with risk averse workers that the higher inflation uncertainty is, the greater is the likelihood of indexation.

response to a supply shock at the beginning and at the end of the “Great Inflation” since high wage indexation pushes nominal wages in the same direction as prices after an inflationary shock.

The rise and fall of wage indexation over time can be linked to the literature that finds a weaker reaction of monetary policy to inflation during the “Great Inflation” and more aggressive inflation stabilization of monetary policy before and after this period (e.g. Clarida et al., 2000). This simultaneous time variation of the inflation reaction parameter in the policy rule and the degree of wage indexation can be regarded as two sides of the same coin, the monetary policy regime. Specifically, a weakly inflation stabilizing policy rule is conducive to high and volatile inflation. This fosters the use of wage indexation clauses as protection against inflation uncertainty, which in turn amplifies the effects of inflationary shocks. On the other hand, a regime of price stability reduces the need for protection against inflation uncertainty, thus mitigating wage indexation. A lower degree of wage indexation in turn reduces the effects of inflationary shocks, thus further contributing to price stability.

The fact that the monetary policy regime is not only characterized by the parameters of the monetary policy rule, but also by the wage setting behavior in the labor market, has two important implications for policy analysis. First, counterfactual experiments altering solely the monetary policy rule do not adequately capture the wider consequences of a change in the policy regime. Based on such counterfactual simulations, a number of studies (e.g. Primiceri, 2005; Sims and Zha, 2006; Canova and Gambetti, 2006) conclude that a shift in the monetary policy rule is unable to explain the changes in macroeconomic dynamics and volatility over time, hence questioning the “good monetary policy” hypothesis of the “Great Moderation”. The analysis suggests, however, that the additional effects *via* lower wage indexation and contained second-round effects should also be taken into account. Finally, a second implication is that embedding a certain degree of wage indexation in micro-founded macroeconomic models could be highly misleading when optimal monetary policy or significant regime changes in policy are investigated, as the analysis of this paper shows that the degree of wage indexation is not structural in the sense of Lucas (1976).

Acknowledgments

We would like to thank an anonymous referee, Luca Benati, Julio Carrillo, Mikael Carlsson, Giorgio Primiceri, Frank Smets, Mathias Trabandt and conference and seminar participants at the SED Annual Meeting 2011, the CREI/CEPR workshop on “Changes in Labour Market Dynamics”, the Euro Area Wage Dynamics Network, and seminar participants at the European Central Bank, Magyar Nemzeti Bank, University of Münster, University of Padua, ECARES and the University of Tilburg for helpful comments. The views expressed are solely our own and do not necessarily reflect those of the BIS, the ECB or the Eurosystem.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at <http://dx.doi.org/10.1016/j.jmoneco.2012.10.009>.

References

- Basu, S., Fernald, J., Kimball, G., 2006. Are technology improvements contractionary? *American Economic Review* 96, 1418–1448.
- Baumeister, C., Peersman, G., 2008. Time-Varying Effects of Oil Supply Shocks on the US Economy. Ghent University Working Paper 08/515.
- Benati, L., 2008. Investigating inflation persistence across monetary regimes. *Quarterly Journal of Economics* 123, 1005–1060.
- Benati, L., Mumtaz, H., 2007. U.S. Evolving Macroeconomic Dynamics: A Structural Investigation. ECB Working Paper 746.
- Bernanke, B., 2006. The Benefits of Price Stability. Speech held at the Center for Economic Policy Studies and on the Occasion of the Seventy-Fifth Anniversary of the Woodrow Wilson School of Public and International Affairs. Princeton University, Princeton, New Jersey.
- Bilbiie, F., Straub, R. Asset market participation, monetary policy rules and the great inflation. *Review of Economics and Statistics*, http://dx.doi.org/10.1162/REST_a_00254, in press.
- Blanchard, O., Simon, J., 2001. The long and large decline in U.S. output volatility. *Brookings Papers on Economic Activity* 32, 135–174.
- Canova, F., Gambetti, L., 2006. Structural Changes in the US Economy: Bad Luck or Bad Policy? CEPR Discussion Paper 5457.
- Christiano, L., Eichenbaum, M., Evans, C., 2005. Nominal rigidities and the dynamic effects of monetary policy. *Journal of Political Economy* 113.
- Christiano, L., Trabandt, M., Walentin, K., 2011. DSGE models for monetary policy analysis. in: Friedman, B., Woodford, M. (Eds.), *Handbook of Monetary Economics*, Elsevier, Amsterdam, pp. 285–367.
- Clarida, R., Gali, J., Gertler, M., 2000. Monetary policy rules and macroeconomic stability: evidence and some theory. *Quarterly Journal of Economics* 115, 147–180.
- Cogley, T., Sargent, T., 2002. Evolving post-WWII U.S. inflation dynamics. in: Bernanke, B., Rogoff, K. (Eds.), *NBER Macroeconomics Annual 2001*, MIT Press, Cambridge, MA, pp. 331–347.
- Cogley, T., Sargent, T., 2005. Drift and volatilities: monetary policies and outcomes in the post WWII US. *Review of Economic Dynamics* 8, 262–302.
- Davis, S., Kahn, J., 2008. Interpreting the Great Moderation: Changes in the Volatility of Economic Activity at the Macro and Micro Levels. FRB of New York Staff Report 334.
- Dedola, L., Neri, S., 2007. What does a technology shock do? A VAR analysis with model-based sign restrictions. *Journal of Monetary Economics* 54, 512–549.
- Ehrenberg, R., Danziger, L., San, G., 1984. Cost-of-living adjustment clauses in union contracts. *Research in Labor Economics* 6, 1–63.
- Gali, J., 1999. Technology, employment and the business cycle: do technology shocks explain aggregate fluctuations?. *American Economic Review* 89, 249–271.
- Gali, J., Gertler, M., 1999. Inflation dynamics: a structural econometric analysis. *Journal of Monetary Economics* 44, 195–222.

- Galí, J., López-Salido, D., Vallés, J., 2003. Technology shocks and monetary policy: assessing the Fed's performance. *Journal of Monetary Economics* 50, 723–743.
- Gambetti, L., Pappa, E., Canova, F., 2008. The structural dynamics of US output and inflation: what explains the changes?. *Journal of Money, Credit and Banking* 40, 369–388.
- Holland, S., 1986. Wage indexation and the effect of inflation uncertainty on employment: an empirical analysis. *American Economic Review* 76, 235–243.
- Holland, S., 1988. The changing responsiveness of wages to price-level shocks: explicit and implicit indexation. *Economic Inquiry* 26, 265–279.
- Holland, S., 1995. Inflation and wage indexation in the postwar United States. *The Review of Economics and Statistics* 77, 172–176.
- Judd, J., Rudebusch, G., 1999. Taylor's rule and the fed: 1970–1997. *Federal Reserve Bank of San Francisco Economic Review* 3, 3–16.
- Justiniano, A., Primiceri, G., 2008. The time-varying volatility of macroeconomic fluctuations. *American Economic Review* 98, 604–641.
- Kang, K., Kim, C.-J., Morley, J., 2009. Changes in U.S. inflation persistence. *Studies in Nonlinear Dynamics & Econometrics* 13. (Article 1).
- Liu, Z., Phaneuf, L., 2007. Technology shocks and labor market dynamics: some evidence and theory. *Journal of Monetary Economics* 54, 2534–2553.
- Lubik, T., Schorfheide, F., 2004. Testing for indeterminacy: an application to US monetary policy. *American Economic Review* 94, 190–217.
- Lucas, R., 1976. Econometric policy evaluation: a critique. *Carnegie-Rochester Conference Series on Public Policy* 1, 19–46.
- McConnell, M., Perez-Quiros, G., 2000. Output fluctuations in the United States: what has changed since the early 1980s?. *American Economic Review* 90, 1464–1476.
- Orphanides, A., 2003. Historical monetary policy analysis and the Taylor Rule. *Journal of Monetary Economics* 50, 983–1022.
- Peersman, G., 2005. What caused the early millennium slowdown? Evidence based on vector autoregressions. *Journal of Applied Econometrics* 20, 185–207.
- Peersman, G., Straub, R., 2009. Technology shocks and robust sign restrictions in a Euro Area SVAR. *International Economic Review* 50, 727–750.
- Primiceri, G., 2005. Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies* 72, 821–852.
- Ragan, J., Bratsberg, B., 2000. Why have cost-of-living clauses disappeared from union contracts and will they return? *Southern Economic Journal* 67, 304–324.
- Rubio-Ramírez, J., Waggoner, D., Zha, T., 2010. Structural vector autoregressions: theory of identification and algorithms for inference. *Review of Economic Studies* 77, 665–696.
- Sims, C., Zha, T., 2006. Were there regime switches in US monetary policy? *American Economic Review* 96, 54–81.
- Smets, F., Wouters, R., 2007. Shocks and frictions in US business cycles: a Bayesian DSGE approach. *American Economic Review* 97, 586–606.
- Stock, J., Watson, M., 2002. Has the business cycle changed and why?. in: Bernanke, B., Rogoff, K. (Eds.), *NBER Macroeconomics Annual 2002*, MIT Press, Cambridge, MA, pp. 152–230.