The Interplay of Wage Mark-Up and Price Mark-Up Shocks in Shaping U.S. Economic Dynamics

*

Eric Ayamga†

December 16, 2024

Abstract

Using a medium-scale Dynamic Stochastic General Equilibrium (DSGE) model, this study examines the main economic shocks affecting output, inflation, and wage growth in the US economy. The study, which makes use of principal component analysis and Bayesian estimating techniques, finds that while monetary policy and risk premium shocks have a higher impact in the short term, productivity shocks are the main driver of long-term economic activity. The results provide new insights into how wage and price markup shocks affect U.S. economic variations and validate their important roles. This study improves the accuracy of shock decomposition and parameter estimates by resolving a number of identifying issues that arise in economic modeling.

Keywords: Economic fluctuation, shock, DSGE models, identification
JEL: E12, E3, E32

***Declarations of interest:** none.

†Texas Tech University, Department of Economics, P. O. Box 41014 Lubbock-Texas 79409-1014, United States, e-mail: eayamga@ttu.edu

1 Introduction

The question of what shock drives the US economy remains a puzzle to macroeconomists. Since Sims (1980*b*) and Kydland & Prescott (1982), this question has been the fundamental question in modern dynamic macroeconomics (Justiniano et al., 2010). Despite its importance, the field has not reached a consensus on the answer. The question many macroeconomists and policymakers ask is was Cochrane right when he stated that "we will forever remain ignorant of the fundamental causes of economic fluctuations" (Cochrane (1994). After 30 years, the field still has no answer to this question. Macroeconomists have diverse views of the shocks that drive fluctuations in output and inflation in the US. One trend of the literature focuses on the importance of technology in driving fluctuations in output and inflation. After Sims (1980*b*) introduced vector autoregression linking innovation to a linear system and macroeconomic shocks; Kydland & Prescott (1982) expanded it to include non-policy shock (i.e. technology shock). The authors argued that technology shock is the most important driver of economic fluctuations. Similarly, Prescott (1986) used the Solow residual as a measure of total factor productivity (TFP) shock and argued that bulk of business cycle fluctuations are explained by technology shocks. Smets & Wouters (2007) estimated a bayesian DSGE model with seven shocks and find that technology shock is the most important shock that drives economic fluctuations. However, McGrattan (1994) showed that the importance of technology shock diminishes when fiscal shocks are included.

Much of the literature focuses on the relevance of monetary policy shocks in explaining economic fluctuations. For instance, Sims (1972) and Barro (1977, 1978) show that fluctuations in money supply could explain a crucial fraction of output. However, later Sims (1980*a*) and Litterman & Weiss (1985) discovered that inclusion of interest rates in the VAR model reduces the importance of money. Bernanke & Blinder (1992) argued that interest rate is the key monetary policy tool. Contrary, Khan & Tsoukalas (2012) and Justiniano et al. (2011) show that unanticipated marginal efficiency of investment shocks drive economic fluctuations. Khan & Tsoukalas (2012) and Schmitt-Grohé & Uribe (2012) find wage markup news shocks to account for more than half of variances of hours work, following the earlier study by Shapiro & Watson (1988). Shapiro & Watson (1988) found labor supply shocks to be the dominant driver of business cycles. Most of the literature also identifies other shocks as important drivers of economic fluctuations. For instance, Hamilton (1983, 2003) and Davis & Haltiwanger (2001) argued that oil supply shocks are the major drivers of economic fluctuations; Ben Zeev & Khan (2015) showed that news about investment-specific technology shock drives output and price fluctuations. McGrattan (1994), Blanchard & Perotti (2002), and Mountford & Uhlig (2009) demonstrate that fiscal policies are the main drivers of economic fluctuations.

Although a significant progress has been made since Cochrane (1994), we remain unaware of the dominant drivers of economic fluctuations. Therefore, this study contributes to the existing literature by using a novel approach to measure and identify economic variables in our Dynamic Stochastic General Equilibrium (DSGE) model. In this study, I introduced a novel way of measuring the seven observables in Smets & Wouters (2007) and Justiniano et al. (2011) used in related literature to correctly map observables to model variables. Iskrev (2010*a*,*b*) argued that some identification failures can be due to data limitations, such as lack of observations for some variables, or data deficiencies. In this study, I focus on the later. Data deficiency played an important role in the diverse answers to the question of which shocks drive economic fluctuations. For instance, Smets & Wouters (2007) and Justiniano et al. (2011) measured investment differently and arrived at different conclusions although their models are the same. Although, we acknowledge the fact that some models are unidentified or weakly identified before taking to the data (Iskrev, 2010). I calibrated the weakly identified parameters in Smets & Wouters (2007) and focused on solving identification issues rising from data deficiency.

Similar to Smets & Wouters, (2007), Prescott, (1986), and Kydland & Prescott, (1982)), we confirm that productivity shock still remains a strong driver of economic activity in the United States. However, following Christiano et al. (2005) we show that monetary policy shocks are only relevant in the short run. We also conffirm the findings of Khan & Tsoukalas (2012) and Schmitt-Grohé & Uribe (2012), who found wage markup news shocks to account for more than half of variances of hours work, following an earlier study by Shapiro & Watson (1988). Most importantly, none of the existing literature to the best of our knowledge demonstrates the importance of price-mark-up shocks in driving economic activities in the United States.

2 Model

I used a medium-scale DSGE model from Smets & Wouters (2004, 2007) in this study. Below is a detail description of the model:

2.1 Households

Households choose consumption plan C_t, hours worked L_t, bonds B_t, investment I_t, and capital utilization Z_t to maximize lifetime utility subject to all constraints as follows:

Household j maximizes the following objective function:

$$\max\ E_t \sum_{s=0}^{\infty} \beta^s \left[\frac{1}{1-\sigma_c} \left(C_{t+s}(j) - \lambda C_{t+s-1} \right)^{1-\sigma_c} \right] \exp\left(\frac{\phi}{1+\sigma_l} L_{t+s}(j)^{1+\sigma_l} \right) \tag{1}$$

Subject to the budget constraint:

$$C_{t+s}(j) + I_{t+s}(j) + \frac{B_{t+s}(j)}{\epsilon_t^b R_t + s P_{t+s}} - T_t = \frac{B_{t+s-1}(j)}{P_{t+s}} + \frac{W_{t+s}^h(j) L_{t+s}(j)}{P_{t+s}} + \frac{R_{t+s}^k(t) Z_{t+s}(j) K_{t+s-1}(j)}{P_{t+s}} \tag{2}$$

$-a(Z_{t+s}(j))K_{t+s-1}(j) + \frac{Div_{t+s}}{P_{t+s}}$

And the capital accumulation equation:

$$K_t(j) = (1-\delta)K_{t-1}(j) + \varepsilon_t^i \left[1 - S\left(\frac{I_t(j)}{I_{t-1}(j)} \right) \right] I_t(j) \tag{3}$$

The parameter λ captures external habit formation. The one-period bond is expressed on a discount basis. ϵ_t^b an exogenous premium in bond returns, may be a result of financial sector inefficiencies that result in a premium on the deposit rate relative to the central bank's risk-free rate or a risk premium that households must pay in order to keep one-period bonds. According to the stochastic process, ε_t^b:

$$\ln \varepsilon_t^b = \rho_b \ln \varepsilon_{t-1}^b + \eta_t^b \quad \text{where} \quad \eta_t^b \sim \mathcal{N}(0, \sigma_b) \tag{4}$$

Where δ is the depreciation rate, $S(.)$ is the adjustment cost of investment function, with $S(1) = 0$, $S^{‘}(1) = 0$, $S^{“}(.) \geq 0$, T_{t+s} is lump sum taxes or subsidies, Div_t is the dividends distributed by the labor unions, and ε_t^i is a stochastic shock to the price of investment relative to consumption goods and follows an exogenous process:

$$\ln \varepsilon_t^i = \rho_i \ln \varepsilon_{t-1}^i + \eta_t^i \quad \text{where} \quad \eta_t^i \sim \mathcal{N}(0, \sigma_i) \tag{5}$$

Finally, households choose the utilization rate of their capital. The amount of effective capital that households can rent to the firms is:

$$K_t^s(j) = Z_t(j) K_{t-1}(j) \tag{6}$$

Households earn $R_t^k Z_t(j) K_{t-1}(j)$ as income from renting capital services, while they pay $P_t a(Z_t(j)) K_{t-1}(j)$ as the cost of capital utilization. In equilibrium households will make the same choices for consumption, hours worked, bonds, investment, and capital utilization.

2.2 Final Goods Producers

The final good Y_t is a composite made of a continuum of intermediate goods $Y_t(i)$ as in Kimball (1995). The final good producers buy intermediate goods on the market, package Y_t, and resell it to consumers, investors, and the government in a perfectly competitive market.

The final good producers maximize profits. Their problem is:

$$\max_{Y_t, Y_t(i)} \quad P_t Y_t - \int_0^1 P_t(i) Y_t(i)\, di \tag{7}$$

$$\text{s.t.} \quad \left[\int_0^1 G\left(\frac{Y_t(i)}{Y_t}, \phi_{p,t} \right) di \right] = 1 \quad (\lambda_{f,t}), \tag{8}$$

where P_t and $P_t(i)$ are the prices of the final and intermediate goods, respectively, and G is a strictly concave and increasing function characterized by $G(1) = 1$. $\phi_{p,t}$ is an exogenous process reflecting shocks to the aggregator function that result in changes in the elasticity of demand and therefore in the markup. We constrain $\phi_{p,t} \in (0,1)$, and it follows the exogenous ARMA process:

$$\ln \phi_{p,t} = (1-\rho_p)\ln \phi_p + \rho_p \ln \phi_{p,t-1} - \eta_p \epsilon_{p,t-1} + \epsilon_{p,t}, \quad \epsilon_{p,t} \sim N(0, \sigma_p^2). \tag{9}$$

To simplify notation, we leave out this argument in what follows.

The first-order conditions (FOCs) are:

$$\frac{\partial \mathcal{L}}{\partial Y_t}: \quad P_t = \lambda_{f,t} Y_t \int_0^1 G'\left(\frac{Y_t(i)}{Y_t}\right)\frac{Y_t(i)}{Y_t}\, di, \tag{10}$$

$$\frac{\partial \mathcal{L}}{\partial Y_t(i)}: \quad P_t(i) = \lambda_{f,t} G'\left(\frac{Y_t(i)}{Y_t}\right)\frac{1}{Y_t}, \tag{11}$$

resulting in:

$$Y_t(i) = Y_t G'^{-1}\left(\frac{P_t(i)}{P_t}\int_0^1 G'\left(\frac{Y_t(i)}{Y_t}\right)\frac{Y_t(i)}{Y_t}\, di\right). \tag{12}$$

As in Kimball (1995), the assumptions on G imply that the demand for input $Y_t(i)$ is decreasing in its relative price, while the elasticity of demand is a positive function of the relative price (or a negative function of the relative output).

2.3 Intermediate Goods Producers

Intermediate good producer i uses the following technology:

$$Y_t(i) = \varepsilon_{a,t} K_t^s(i)^{\alpha}\left(\bar{\ell}_t L_t(i)\right)^{1-\alpha} - \Phi, \tag{13}$$

where $K_t^s(i)$ is capital services used in production, $L_t(i)$ is aggregate labor input, and Φ is a fixed cost. $\bar{\ell}_t$ represents the labor-augmenting deterministic growth rate in the economy, and $\varepsilon_{a,t}$ is total factor productivity following the process:

$$\ln \varepsilon_{a,t} = (1-\rho_z)\ln \varepsilon_a + \rho_z \ln \varepsilon_{a,t-1} + \epsilon_{a,t}, \quad \epsilon_{a,t} \sim N(0, \sigma_a^2). \tag{14}$$

The firm's profit is given by:

$$\Pi_t(i) = P_t(i)Y_t(i) - W_t L_t(i) - R_t^k K_t(i), \tag{15}$$

where W_t is the aggregate nominal wage rate and R_t^k is the rental rate on capital.

Cost minimization yields the conditions:

$$\frac{\partial \mathcal{L}}{\partial L_t(i)} : \quad MC_t(i)\frac{(1-\alpha)\varepsilon_{a,t}K_t^s(i)^{\alpha}L_t(i)^{-\alpha}}{\bar{\ell}_t} = W_t, \tag{16}$$

$$\frac{\partial \mathcal{L}}{\partial K_t^s(i)} : \quad MC_t(i)\alpha\varepsilon_{a,t}K_t^s(i)^{\alpha-1}L_t(i)^{1-\alpha} = R_t^k, \tag{17}$$

where $MC_t(i)$ is the marginal cost of production.

Combining these FOCs and noting that the capital-labor ratio is equal across firms implies:

$$\frac{K_t^s}{L_t} = \frac{\alpha}{1-\alpha}\frac{W_t}{R_t^k}. \tag{18}$$

The marginal cost MC_t is the same for all firms and equals:

$$MC_t = \frac{W_t^{1-\alpha}(R_t^k)^{\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}\varepsilon_{a,t}}. \tag{19}$$

Under Calvo pricing with partial indexation, the optimal price set by the firm that is allowed to re-optimize results from the following problem:

$$\max_{\tilde{P}_t(i)} \quad \mathbb{E}_t\sum_{s=0}^{\infty}(\beta\theta_p)^s\Lambda_{t+s}\left[\tilde{P}_t(i)Q_{t+s|t} - MC_{t+s}Y_{t+s}(i)\right], \tag{20}$$

subject to:

$$Y_{t+s}(i) = Y_{t+s}G'^{-1}\left(\frac{\tilde{P}_t(i)}{P_{t+s}}\int_0^1 G'\left(\frac{Y_{t+s}(j)}{Y_{t+s}}\right)\frac{Y_{t+s}(j)}{Y_{t+s}}\,dj\right), \tag{21}$$

where Λ_{t+s} is the stochastic discount factor and θ_p is the Calvo probability of price rigidity.

The first-order condition is:

$$\mathbb{E}_t\sum_{s=0}^{\infty}(\beta\theta_p)^s\Lambda_{t+s}\left[Q_{t+s|t} - MC_{t+s}\frac{\partial Y_{t+s}(i)}{\partial \tilde{P}_t(i)}\right] = 0. \tag{22}$$

Where $x_t = G'^{-1}(z_t)$ and $z_t = \frac{P_t(i)}{P_t}\pi_t$, the aggregate price index is given by:

$$P_t = (1-\theta_p)P_t(i)G'^{-1}\left(\frac{P_t(i)\pi_t}{P_t}\right) + \theta_p\phi_{p,t-1}^{1-\theta_p}P_{t-1}G'^{-1}\left(\phi_{p,t-1}^{1-\theta_p}\frac{P_{t-1}\pi_t}{P_t}\right). \tag{23}$$

2.4 Intermediate Labor Union Sector

Households supply homogeneous labor to intermediate labor unions, which differentiate labor services and set wages subject to a Calvo scheme. Labor unions negotiate wages with labor packers.

The total labor input L_t used by intermediate goods producers is a composite:

$$L_t = \left(\int_0^1 L_t(l)^{\frac{1}{1+\lambda_w}} \, dl \right)^{1+\lambda_w}, \tag{24}$$

where λ_w reflects the wage markup. Labor packers buy labor from unions and package it for intermediate goods producers, maximizing profits in a perfectly competitive market. From the first-order conditions (FOCs) of the labor packers:

$$L_t(l) = \left(\frac{W_t(l)}{W_t} \right)^{\frac{-1-\lambda_w}{\lambda_w}} L_t, \tag{25}$$

with $W_t(l)$ being the wage set by union l, and W_t the aggregate wage index:

$$W_t = \left(\int_0^1 W_t(l)^{\frac{-1}{\lambda_w}} \, dl \right)^{-\lambda_w}. \tag{26}$$

The wage set by union l follows:

$$W_{t+s}(l) = \tilde{W}_t(l) \prod_{j=1}^{s} \phi_{w,t+j-1}^{1-\phi_w}, \tag{27}$$

where ϕ_w represents the fraction of unions that cannot reoptimize wages in each period.

Labor unions optimize wages to maximize their discounted future utility:

$$\max_{\tilde{W}_t(l)} \mathbb{E}_t \sum_{s=0}^{\infty} (\beta \phi_w)^s \Lambda_{t+s} \left[\tilde{W}_t(l) L_{t+s}(l) - W_t^h L_{t+s}(l) \right], \tag{28}$$

subject to the demand for labor:

$$L_{t+s}(l) = \left(\frac{W_{t+s}(l)}{W_{t+s}} \right)^{\frac{-1-\lambda_w}{\lambda_w}} L_{t+s}. \tag{29}$$

The first-order condition for the optimal wage is:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta \phi_w)^s \Lambda_{t+s} L_{t+s}(l) \left[\tilde{W}_t(l) - \frac{\lambda_w}{1+\lambda_w} W_t^h \right] = 0. \tag{30}$$

2.5 Government Policies

The central bank follows a nominal interest rate rule by adjusting its instrument in response to deviations of inflation and output from their respective target levels:

$$R_t = R^* \left(\frac{R_{t-1}}{R^*} \right)_R^{\rho} (\pi_t)^{\phi_\pi} \left(\frac{Y_t}{Y^*} \right)^{\phi_Y} \exp(\epsilon_t^R), \tag{31}$$

where R^* is the steady-state nominal rate, ρ_R determines the degree of interest rate smoothing, ϕ_π and ϕ_Y represent the central bank's reaction to inflation and output deviations, respectively, and ϵ_t^R is a monetary policy shock.

The government budget constraint is given by:

$$G_t + T_t = \frac{B_t}{1+R_t} - B_{t-1}, \tag{32}$$

where G_t is government spending, T_t is lump-sum taxes, and B_t is government debt.

Government spending as a share of GDP, $g_t = \frac{G_t}{Y_t}$, follows an exogenous AR(1) process:

$$\ln g_t = (1-\rho_g)\ln g^* + \rho_g \ln g_{t-1} + \epsilon_t^g, \tag{33}$$

where g^* is the steady-state government spending share, ρ_g captures persistence, and ϵ_t^g is a fiscal policy shock.

3 Identification

Identification is associated with the capacity to infer parameters from the data and observational equivalency. Let Y be the set of observations and let structure S be a complete probability specification of Y in the form $S = F(Y,\theta)$ where $\theta \in \Theta \subset R^n$ is the vector of parameters, Θ being the parameter space. Two structures, $S^0 = F(Y,\theta^0)$ and $S^* = F(Y,\theta^*)$ are said to be observationally equivalent, if $F(Y,\theta^0) = F(Y,\theta^*)$ for almost all Y . The structure is identified if this equality means $\theta^0 = \theta^*$, and unidentified otherwise. Instead of using less formal parameter calibration, DSGE models are currently usually estimated using formal econometric full- or limited-information methods. Since alternative sets of structural parameters should not produce observationally similar results, parameters must be "identified" in order to get meaningful estimation results. Crucially, identification matters in both the Bayesian and classical (frequentist) approaches to statistical inference. The method seems very useful and can be used for apriori investigation of the model identification before the model is estimated at all Thus, in this section, I address the problem of identification in our model as presented below:

From Figure 4 to Figure 6, we show that at least two of our parameters are weakly identified in the system. From Figure 2 the points in the figures show correlation or collinearity between the parameters. The color legend indicates the degree of collinearity ranging from tick blue as the lowest collinearity close to zero to tick red indicating high to perfect collinearity. We observed collinearity between the persistence term of the risk premium shock (crhob) and the standard deviation of the error risk premium shock, the persistence term of the monetary policy and the standard deviation of the monetary policy shock, and wage and price indexation parameters are also correlated with the wage and price stickiness parameters. Having a lot of tick red points compared to blue in Figure 2 points to how poor the parameters are identified in the model. These parameters led to rank-deficiency due to their collinearity with the Calvo parameters. The method is able to indicate identified and weakly identified patterns of the parameter space, while suggesting whether this is due to lack of influence of the parameter or its interactions with other parameters. Following Andrle (2010), we use a heuristic method for ordering the parameter vector of each element's "identifiability" through the use of rank revealing factorizations in a repeating sub-set selection issue that accounts for parameter confounding and the flatness of the criterion function.

4 Parameter Estimates

The model presented in the previous section is estimated with Bayesian estimation techniques (the Bayesian estimation methodology is extensive discussed in Smets & Wouters (2003)) using seven key macroeconomic quarterly US time series as observable variables. Gross income, consumption, investment, inflation, and interest data are sourced from the St. Loius Fred economic data site. We measure gross income using real gross product product per capita, consumption is real personal consumption per capita, investment is real gross private investment plus consumption of durable goods divided by population above age sixteen, inflation rate is the log difference of personal consumption expenditure index, and interest is the effective federal funds rates adjusted with the shadow rate during periods in which the US economy is bounded by the zero lower bound. Gross income, investment, and consumption are chained to 2017 US dollars value. We take log difference of income, consumption, and investment. Hours and wages come from the Bureau of Labor Statistics (BLS) (hours and hourly compensation for the Non-Farm Business (NFB) sector for all persons). Hourly compensation is divided by the GDP price deflator in order to get the real wage variable. Hours are adjusted to take into account the limited coverage of the NFB sector compared to GDP (the index of average hours for the NFB sector is multiplied with the Civilian Employment (16 years and over). All series are seasonally adjusted. The interest rate is the Federal Funds Rate. Consumption, investment, GDP, wages and hours are expressed in 100 times log. The corresponding measurement equation is:

$$\begin{bmatrix} \Delta \ln Y_t \\ \Delta \ln C_t \\ \Delta \ln I_t \\ \Delta \ln W_t \\ \ln H_t \\ \Delta \ln P_t \\ R_t \end{bmatrix} = \begin{bmatrix} \hat{\gamma} \\ \hat{\gamma} \\ \hat{\gamma} \\ \hat{\gamma} \\ 0 \\ \hat{\pi} \\ \hat{r} \end{bmatrix} + \begin{bmatrix} y_t - y_{t-1} \\ c_t - c_{t-1} \\ i_t - i_{t-1} \\ w_t - w_{t-1} \\ l_t \\ \pi_t \\ r_t \end{bmatrix}$$

Where $\hat{\gamma} = 100(\gamma - 1)$ is the common quarterly trend growth rate to real GDP, consumption, investment and wages, $\hat{\pi} = 100(\Pi - 1)$ is the quarterly steady-state inflation rate and $\hat{r} = 100(\beta^{-1}\gamma^{\sigma_c}\Pi - 1$ is the steady-state nominal interest rate. Given the estimates of the trend growth rate and the steady-state inflation rate, the latter will be determined by the estimated discount rate. We start by maximizing the log posterior function, which combines the likelihood of the data with the previous knowledge about the parameters, in order to determine the mode of the posterior distribution. In a subsequent phase, the Metropolis-Hastings method is employed to assess the model's marginal likelihood and obtain a comprehensive view of the posterior distribution. From 1960:1 to 2024:2, the entire data period is used to estimate the model.

4.1 Posterior Estimates of the Parameters

To estimate the model, we used the prior distributions of Smets & Wouters (2007). We present the mode, the mean, the standard deviation, and the 5 and 95 percentile of the posterior distribution of the parameters obtained from the Metropolis-Hastings algorithm in Table 1. We found that the trend growth rate of real gross domestic product, consumption, investment, and real wage is 0.36 percent. The posterior mean of the steady-state inflation rate over the full sample is about 0.75% on quarterly basis. The mean of the discount rate is estimated to be quite small (0.65% on an annual basis and 0.1602% on a quarterly basis).

Several points about the estimated processes for the exogenous shock variables are worth mentioning (Table 1). All things considered, the data seems to provide a wealth of information about the stochastic processes underlying the exogenous disturbances. The productivity, the government spending and the wage mark-up processes are estimated to be the most persistent with an AR(1) coefficient of 0.99, 0.96 and 0.94 respectively. However, risk premium, marginal efficiency of investment, and monetary policy processes are the least persistent with an AR(1) coefficients of 0.19, 0.29, and 0.26 respectively. The estimated persistence coefficient of monetary policy suggest monetary policy authorities in the United States are more aggressive in either rising or lower interest rates to stabilize the economy than taking a gradual process of lowering or raising interest rates slowly over a long period of time. The mean of the standard error of the shock to the productivity process is 0.76. The high persistence of the productivity and wage mark-up processes implies that at long horizons most of the forecast error variance of the real variables will be explained by those two shocks. In contrast, both the persistence and the standard deviation of the price mark-up and monetary policy shocks are relatively low (0.15 and 0.21 respectively). The estimates of the main behavioral parameters have their posterior means relatively close to the prior assumptions. Capacity utilization cost parameter is the only exception with an extreme posterior mean of 0.0829 compared to the prior assumed value of 0.5.

Table 1: Results from Metropolis-Hastings (parameters)

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
crhoa	beta	0.500	0.2000	0.983	0.0055	0.9741	0.9920
crhob	beta	0.500	0.2000	0.351	0.2590	0.0660	0.8018
crhog	beta	0.500	0.2000	0.971	0.0116	0.9528	0.9908
crhoqs	beta	0.500	0.2000	0.635	0.0642	0.5291	0.7397

(Continued on next page)

Table 1: (continued)

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
$crhoms$	beta	0.500	0.2000	0.194	0.0653	0.0846	0.2996
$crhopinf$	beta	0.500	0.2000	0.975	0.0226	0.9582	0.9967
$crhow$	beta	0.500	0.2000	0.978	0.0121	0.9606	0.9962
$cmap$	beta	0.500	0.2000	0.823	0.0666	0.7289	0.9231
$cmaw$	beta	0.500	0.2000	0.924	0.0268	0.8826	0.9660
$csadjcost$	norm	4.000	1.5000	5.862	1.3783	3.3870	7.9088
$csigma$	norm	1.500	0.3750	1.272	0.1453	1.0465	1.5050
$chabb$	beta	0.700	0.1000	0.726	0.1202	0.5141	0.8671
$cprobw$	beta	0.500	0.1000	0.766	0.0363	0.7059	0.8251
$csigl$	norm	2.000	0.7500	2.436	0.5873	1.4579	3.3798
$cprobp$	beta	0.500	0.1000	0.557	0.0383	0.5000	0.6096
$cindw$	beta	0.500	0.1500	0.513	0.1042	0.3401	0.6829
$cindp$	beta	0.500	0.1500	0.208	0.0822	0.0769	0.3375
$czcap$	beta	0.500	0.1500	0.365	0.0965	0.2060	0.5212
cfc	norm	1.250	0.1250	1.638	0.0823	1.5011	1.7730
$crpi$	norm	1.500	0.2500	1.942	0.1768	1.6495	2.2291
crr	beta	0.750	0.1000	0.878	0.0173	0.8506	0.9069
cry	norm	0.125	0.0500	0.126	0.0273	0.0809	0.1701
$crdy$	norm	0.125	0.0500	0.144	0.0276	0.1002	0.1897
$constepinf$	gamm	0.625	0.1000	0.665	0.1018	0.4978	0.8297
$constebeta$	gamm	0.250	0.1000	0.138	0.0512	0.0548	0.2159
$constelab$	norm	0.000	2.0000	1.123	0.9593	-0.4230	2.6926
$ctrend$	norm	0.400	0.1000	0.494	0.0307	0.4518	0.5346
cgy	norm	0.500	0.2500	0.584	0.0849	0.4441	0.7229
$calfa$	norm	0.300	0.0500	0.194	0.0217	0.1579	0.2294

Table 2: Results from Metropolis-Hastings (standard deviation of structural shocks)

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
ea	invg	0.100	2.0000	0.514	0.0289	0.4661	0.5607
eb	invg	0.100	2.0000	0.297	0.0842	0.1468	0.3965
eg	invg	0.100	2.0000	0.679	0.0331	0.6241	0.7322
eqs	invg	0.100	2.0000	0.553	0.0593	0.4571	0.6509
em	invg	0.100	2.0000	0.234	0.0130	0.2120	0.2542
$epinf$	invg	0.100	2.0000	0.220	0.0241	0.1805	0.2599
ew	invg	0.100	2.0000	0.265	0.0183	0.2347	0.2950

5 Applications

After demonstrating that the estimated model provides a good fit to the macroeconomic data from the United States, we apply it to examine several important macroeconomic problems. We answer the following queries in this area. First, what are the primary factors that influence output? Second, what are the primary factors that drives inflation and wage growth? Third, how do the observables change in response to productivity, price mark-up, and wage mark-up shocks? In turn, we examine these concerns in each subsection.

5.1 What are the primary factors influencing output?

Figure 1 gives the shock decomposition of output at various horizons based on the mode of the model's posterior distribution. In the short run (within year) movements in real gross domestic product are primarily driven by exogenous shocks that affect intertemporal Euler equations (risk premium shock), monetary policy shocks, exogenous spending shocks, and productivity shocks. In the medium term, only productivity, price mark-up, monetary policy, and risk premium shocks are the main drivers of output. When combined, they explain over half of the output forecast error variance for a year. This is consistent with Christiano et al. (2005), that monetary policy shocks drive economic in the short run and medium run. Since they all have a favorable impact on output, they can all be categorized as "demand" shocks. In the long run, output is driven by productivity shocks, price mark-up shocks, and wage mark-up shock. Productivity shock only contributes to more than 50% of the fluctuations in output. This confirms the large literature that identifies the role of productivity shock in driving long run economic activity (eg Smets & Wouters, (2007), Prescott, (1986), Kydland & Prescott, (1982)).

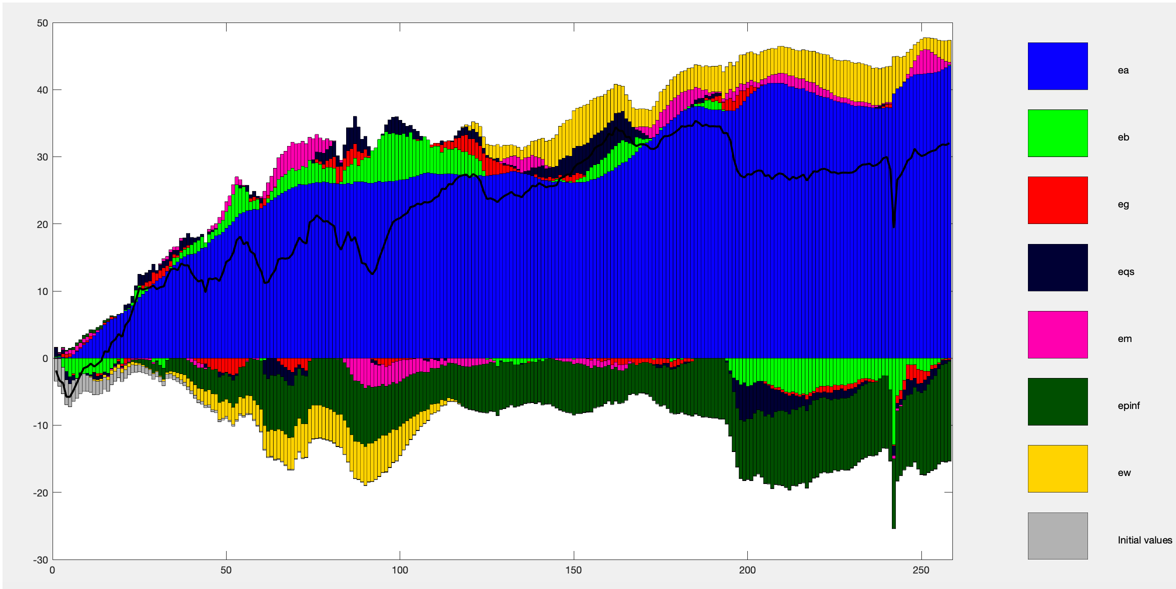


Figure 1: Shock decomposition of output

Note: ea is productivity shock, eb is risk premium shock, eg is exogenous spending shock, em is monetary policy shock, ew is wage mark-up shock, epinf is price mark-up shock, and eqs is marginal efficiency of investment shock

5.2 What drives Prices and Wages?

Just like real GDP, prices and wages are other economic activities that matter most to households and economic policy authorities. Figures 2 and 3 show that productivity shock, price mark-up shock, and wage mark-up shock are the significant drivers of prices and wages in the United States. Although other shocks such as monetary policy shock, risk premium shock, exogenous spending shock, and marginal efficiency of investment shock are relevant in driving economic activities, their impact is relatively small. This confirms the large literature that identifies the role of productivity shock in driving long run economic activity (eg Smets & Wouters, (2007), Prescott, (1986), Kydland & Prescott, (1982)). We also conffirm the findings of Khan & Tsoukalas (2012) and Schmitt-Grohé & Uribe (2012), who found wage markup news shocks to account for more than half of variances of hours work, following an earlier study by Shapiro & Watson (1988). None of the existing literature to the best of our knowledge demonstrates the importance of price-mark-up shocks in driving economic activities in the United States.

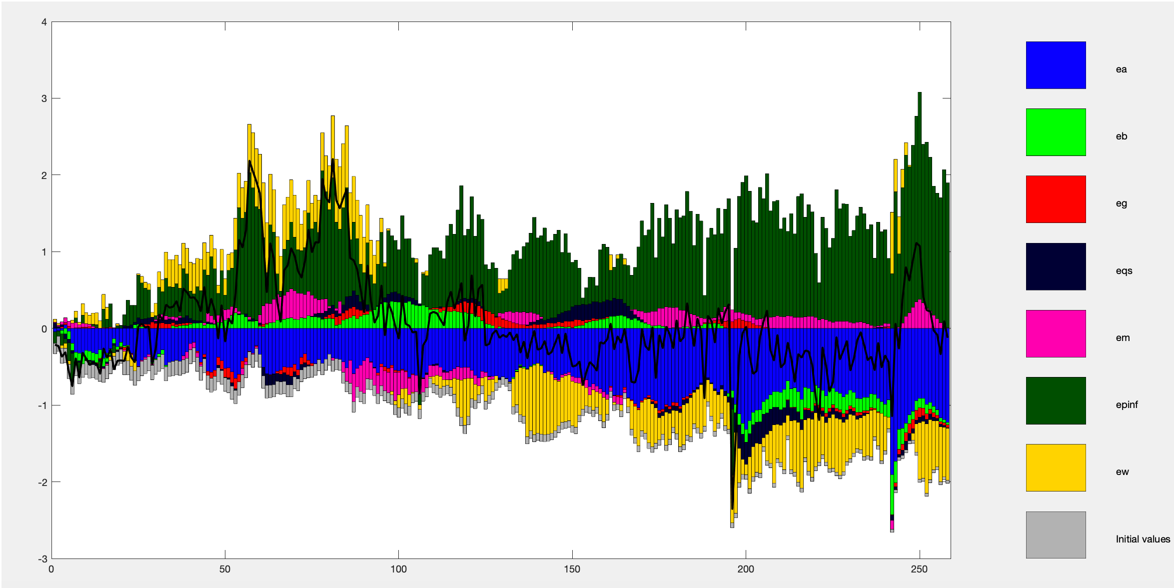


Figure 2: Shock decomposition of inflation

Note: ea is productivity shock, eb is risk premium shock, eg is exogenous spending shock, em is monetary policy shock, ew is wage mark-up shock, epinf is price mark-up shock, and eqs is marginal efficiency of investment shock

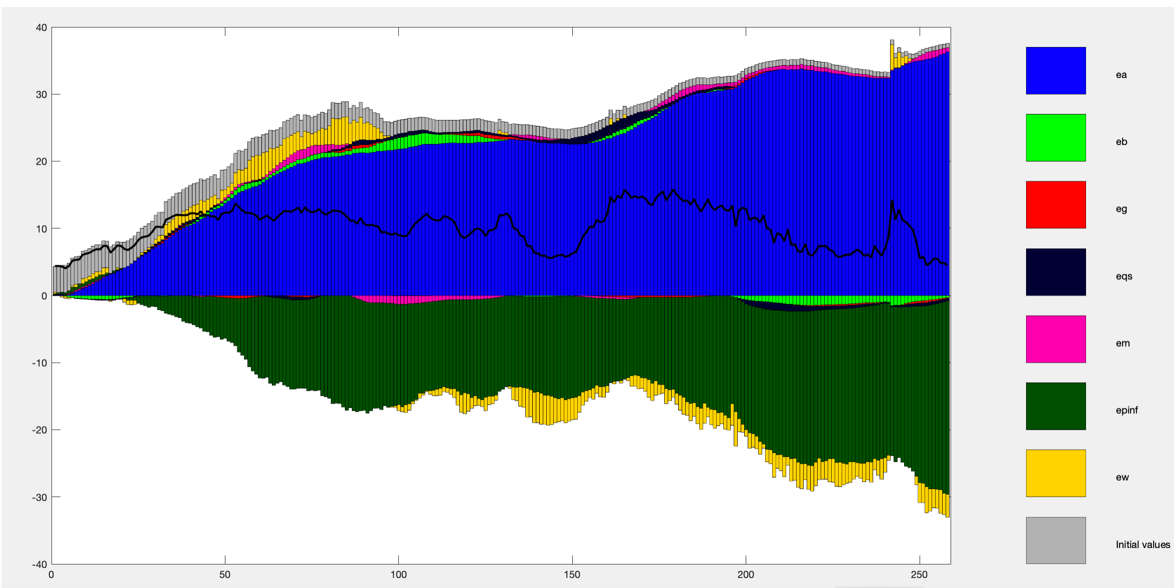


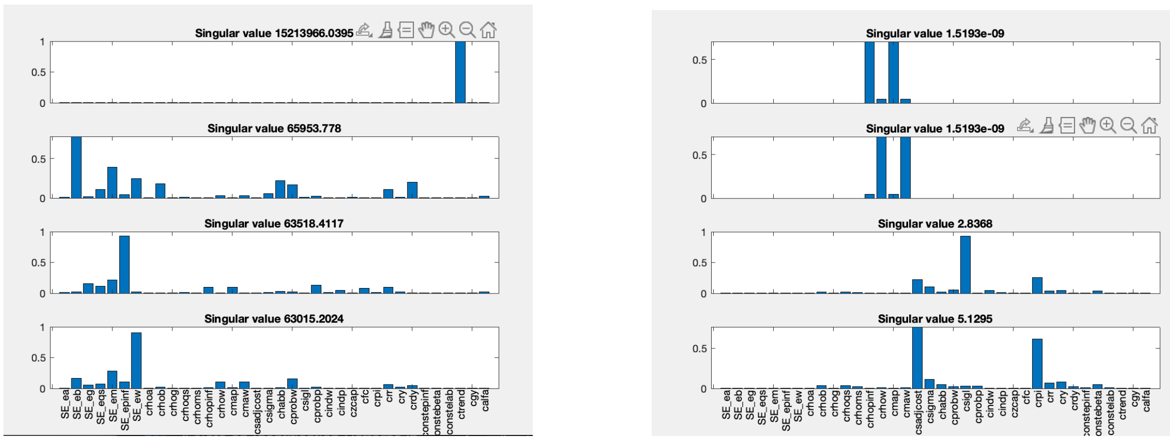
Figure 3: Shock decomposition of Wage

Note: ea is productivity shock, eb is risk premium shock, eg is exogenous spending shock, em is monetary policy shock, ew is wage mark-up shock, epinf is price mark-up shock, and eqs is marginal efficiency of investment shock

6 Conclusion

Using advances in DSGE modeling and parameter identification techniques, this paper offers a thorough analysis of the shocks causing economic fluctuations in the U.S. In addition to addressing data and model misidentification issues, we highlight the critical roles of wage and price mark-up shocks, which were previously understudied in the context of U.S. economic fluctuations. By improving the mapping of observables to model variables and resolving collinearity in parameter estimation, this study not only advances our understanding of economic dynamics but also provides methodological improvements for future macroeconomic research.

Appendix

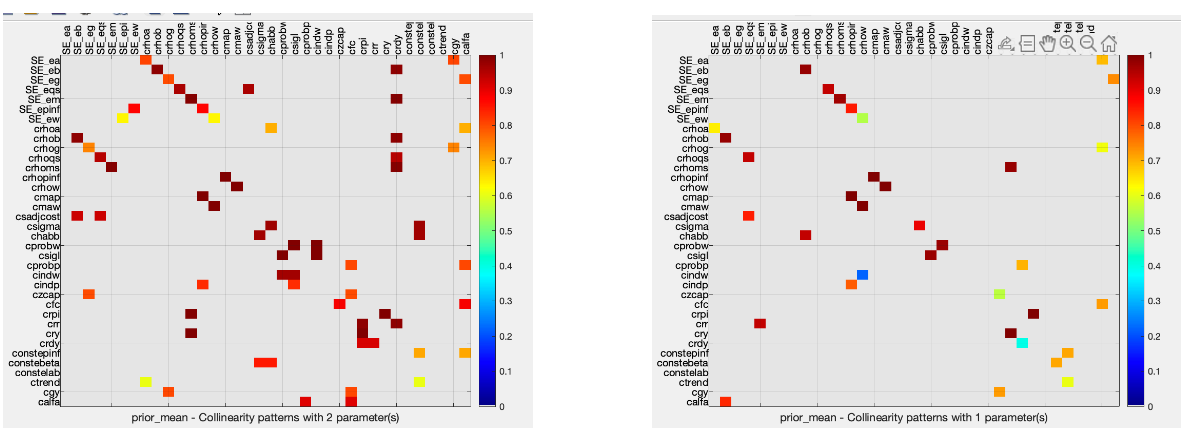


(a) Prior mean - identification patterns

(b) Prior mean - identification patterns

Figure 4: Prior mean identification patterns (Information matrix)

Note:

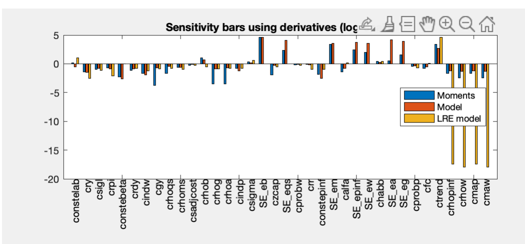


(a) Prior Mean - Collinearity Patterns with 2 parameters

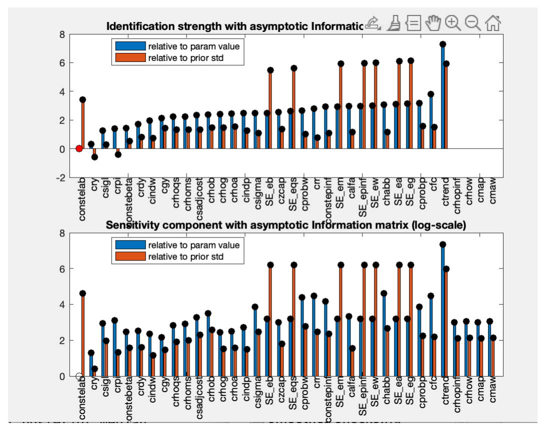
(b) Prior Mean - Collinearity patterns with 1 parameter(s)

Figure 5: Prior mean Collinearity patterns with parameters

Note: The points in the figure show correlation or collinearity between the parameters. The color legend indicates the degree of collinearity ranging from tick blue as the lowest collinearity close to zero to tick red indicating high to perfect collinearity.



(a) Prior Mean - Sensitivity plot



(b) Prior Mean - Identification using information from observables

Figure 6: Prior mean sensitivity plot

Note: The figure shows sensitivity bars of the parameters using log derivatives. The blue bars represent sensitivity to parameter moments log derivatives, red represent sensitivity to model, and yellow represent sensitivity to LRE model.

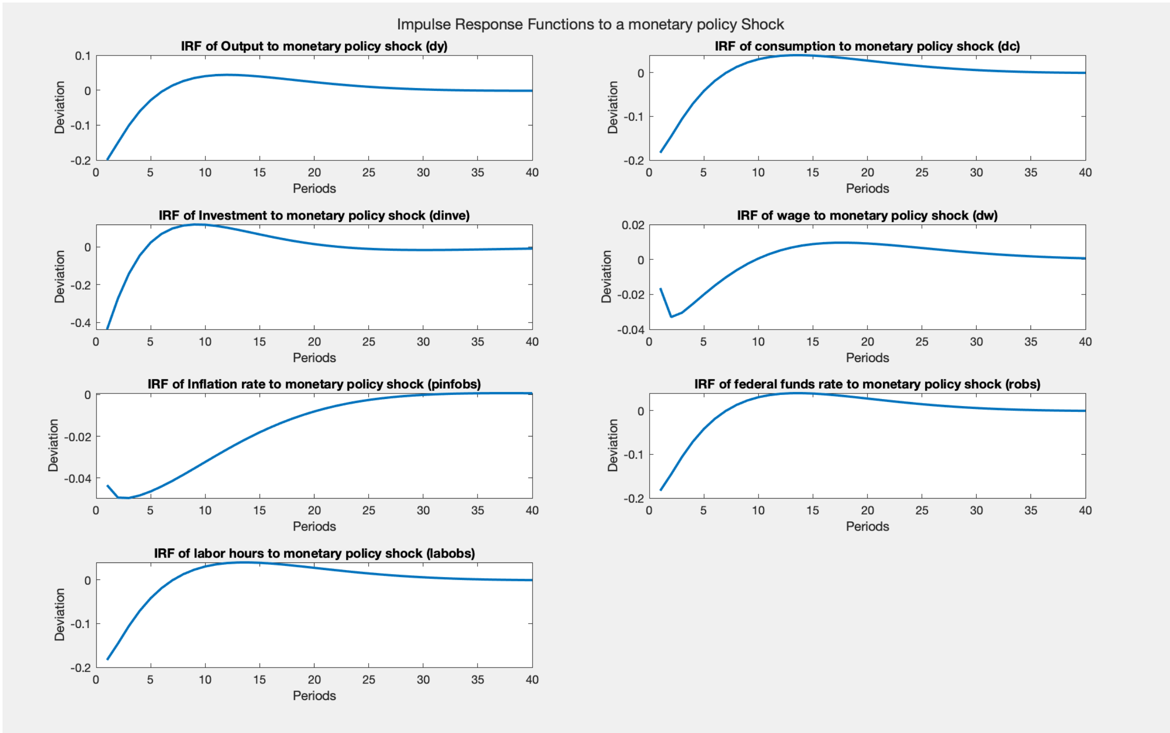


Figure 7: Impulse responses to a monetary policy shock

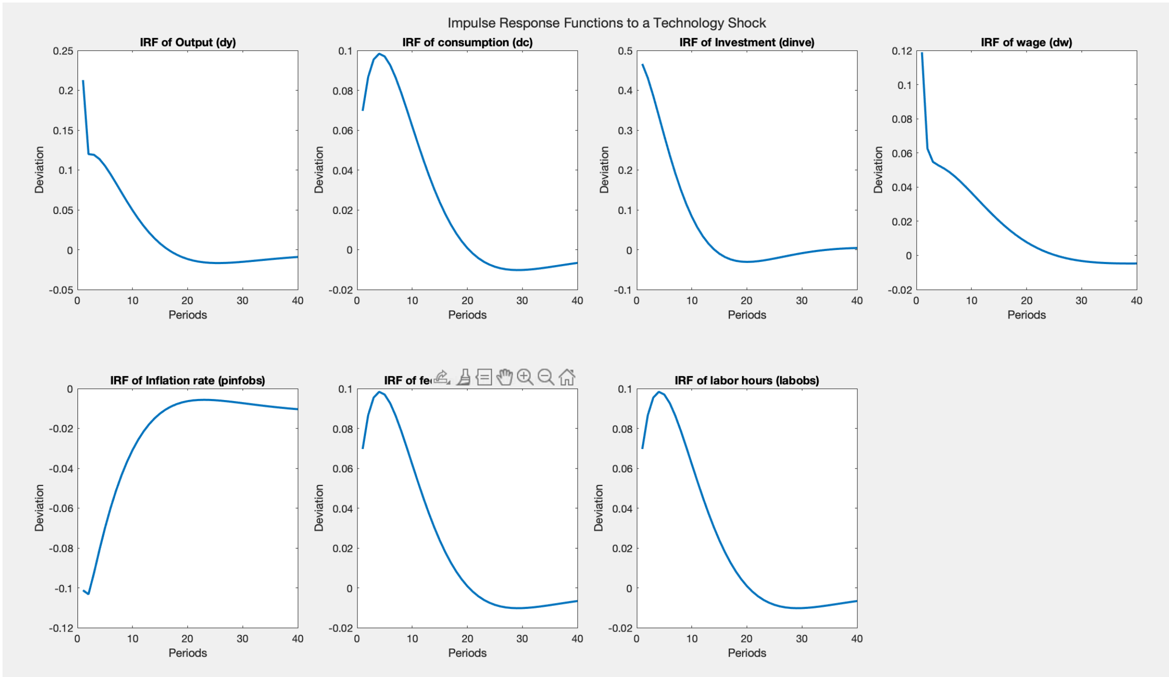


Figure 9: Impulse response functions to a productivity shock

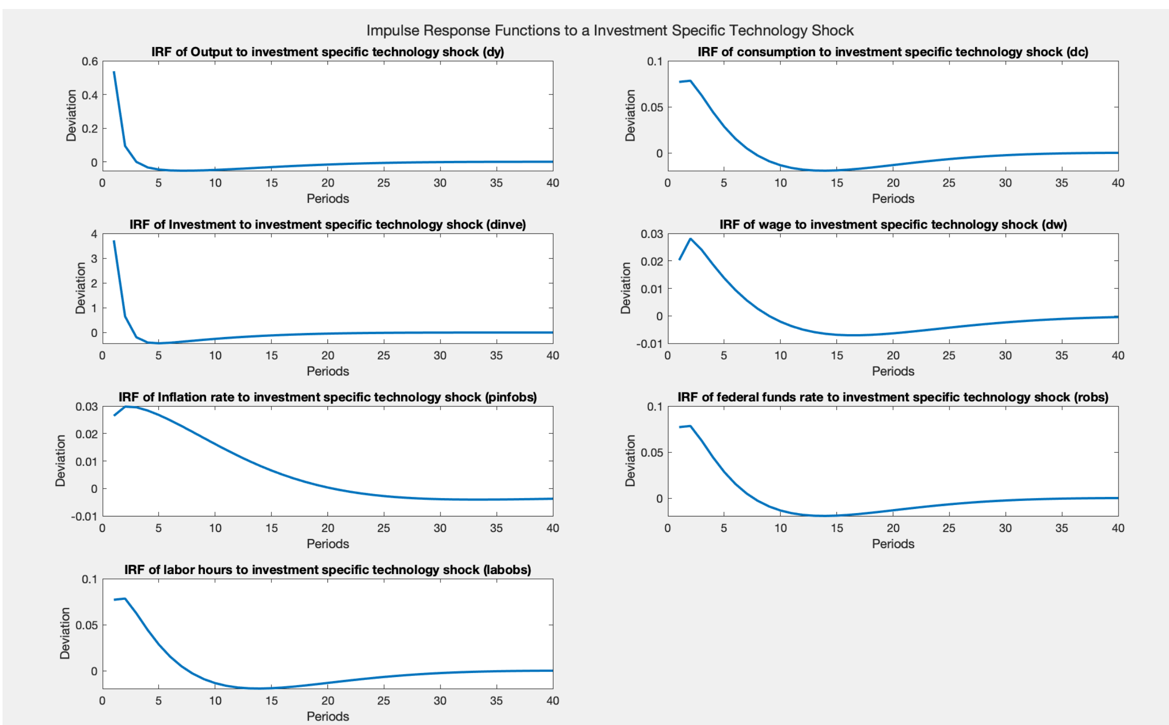


Figure 8: Impulse response functions to a marginal efficiency of investment shock

References

Andrle, M. (2010), 'A note on identification patterns in dsge models'.

Barro, R. J. (1977), 'Unanticipated money growth and unemployment in the united states', *Beihefte zu Kredit und Kapital* p. 186.

Barro, R. J. (1978), 'Unanticipated money, output, and the price level in the united states', *Journal of political economy* **86**(4), 549–580.

Ben Zeev, N. & Khan, H. (2015), 'Investment-specific news shocks and us business cycles', *Journal of Money, Credit and Banking* **47**(7), 1443–1464.

Bernanke, B. & Blinder, A. S. (1992), 'of monetary transmission', *The American Economic Review* **82**(4), 901–921.

Blanchard, O. & Perotti, R. (2002), 'An empirical characterization of the dynamic effects of changes in government spending and taxes on output', *the Quarterly Journal of economics* **117**(4), 1329–1368.

Christiano, L. J., Eichenbaum, M. & Evans, C. L. (2005), 'Nominal rigidities and the dynamic effects of a shock to monetary policy', *Journal of political Economy* **113**(1), 1–45.

Cochrane, J. H. (1994), Shocks, *in* 'Carnegie-Rochester Conference series on public policy', Vol. 41, Elsevier, pp. 295–364.

Davis, S. J. & Haltiwanger, J. (2001), 'Sectoral job creation and destruction responses to oil price changes', *Journal of monetary economics* **48**(3), 465–512.

Hamilton, J. D. (1983), 'Oil and the macroeconomy since world war ii', *Journal of political economy* **91**(2), 228–248.

Hamilton, J. D. (2003), 'What is an oil shock?', *Journal of econometrics* **113**(2), 363–398.

Iskrev, N. (2010*a*), 'Local identification in dsge models', *Journal of Monetary Economics* **57**(2), 189–202.

Iskrev, N. (2010*b*), 'Parameter identification in dynamic economic models', *Economic Bulletin Autumn, Banco de Portugal: Economics and Research Department* .

Justiniano, A., Primiceri, G. E. & Tambalotti, A. (2010), 'Investment shocks and business cycles', *Journal of Monetary Economics* **57**(2), 132–145.

Justiniano, A., Primiceri, G. E. & Tambalotti, A. (2011), 'Investment shocks and the relative price of investment', *Review of Economic Dynamics* **14**(1), 102–121.

Khan, H. & Tsoukalas, J. (2012), 'The quantitative importance of news shocks in estimated dsge models', *Journal of Money, Credit and Banking* **44**(8), 1535–1561.

Kydland, F. E. & Prescott, E. C. (1982), 'Time to build and aggregate fluctuations', *Econometrica: Journal of the Econometric Society* pp. 1345–1370.

Litterman, R. B. & Weiss, L. (1985), 'Your use of the jstor archive indicates your acceptance of jstor's terms and conditions of use, available at', *Econometrica* **53**(1), 129–156.

McGrattan, E. R. (1994), 'The macroeconomic effects of distortionary taxation', *Journal of Monetary Economics* **33**(3), 573–601.

Mountford, A. & Uhlig, H. (2009), 'What are the effects of fiscal policy shocks?', *Journal of applied econometrics* **24**(6), 960–992.

Prescott, E. C. (1986), Theory ahead of business-cycle measurement, *in* 'Carnegie-Rochester conference series on public policy', Vol. 25, Elsevier, pp. 11–44.

Schmitt-Grohé, S. & Uribe, M. (2012), 'What's news in business cycles', *Econometrica* **80**(6), 2733–2764.

Shapiro, M. D. & Watson, M. W. (1988), Sources of business cycle, Technical report, Citeseer.

Sims, C. A. (1972), 'Money, income, and causality', *The American economic review* **62**(4), 540–552.

Sims, C. A. (1980*a*), 'Comparison of interwar and postwar business cycles: Monetarism reconsidered'.

Sims, C. A. (1980*b*), 'Macroeconomics and reality', *Econometrica: journal of the Econometric Society* pp. 1–48.

Smets, F. & Wouters, R. (2004), 'Forecasting with a bayesian dsge model: an application to the euro area', *JCMS: Journal of Common Market Studies* **42**(4), 841–867.

Smets, F. & Wouters, R. (2007), 'Shocks and frictions in us business cycles: A bayesian dsge approach', *American economic review* **97**(3), 586–606.