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Abstract

This paper examines the time varying impact of technology news shocks on the U.S. economy during the Post-World War II era using a structural time varying parameter vector autoregressive (TVP-VAR) model. The identification restrictions are derived from a standard new Keynesian dynamic stochastic general equilibrium (DSGE) model and hold for a wide range of parameter constellations. In addition, the set of restrictions is sufficient to discriminate technology news shocks from other supply and demand side disturbances - technology surprise shocks among them. Overall, there is little evidence that the variance of technology news shocks or their transmission to real activity and inflation has changed over time. However, I detect significant time variation in the endogenous monetary policy reaction to technology news shocks; responding strongly to inflation most of the time, but less during the *Great Inflation* period. The evidence of this paper thus supports the hypothesis that the high inflation rates of the mid and late 1970s were the result of *bad policy* rather than *bad luck*.

Keywords: technology news shocks, business cycles, monetary policy, DSGE models, structural time varying parameter VARs

JEL-Codes: C11, E32, E52

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1 Introduction

There is a growing literature on news about future changes in aggregate technology - *technology news shocks* - and their role in explaining business cycle fluctuations. Technology news shocks do not affect aggregate technology contemporaneously - as *technology surprise shocks* do - but are incorporated into the decision making of forward-looking households and firms. Good news about future aggregate technology increases expected income, so households expand their consumption today. Moreover, firms face lower expected marginal costs and thus cut their prices. In recent theoretical papers, Schmitt-Grohé and Uribe (2008), Jaimovich and Rebelo (2009) as well as Christiano, Ilut, Motto, and Rostagno (2010) introduce technology news shocks into standard business cycle models and argue that these are a potentially important source for aggregate fluctuations. Empirical contributions using vector autoregressions include Beaudry and Portier (2006), who find that future changes in aggregate technology are instantaneously reflected by today's stock returns. Furthermore, Fratzscher and Straub (2010) demonstrate the importance of technology news shocks in explaining current account fluctuations, while Barsky and Sims (2011) reassess the relevance of news driven business cycles.

In this paper I examine the time varying impact of technology news shocks on the U.S. economy during the Post-World War II era using a structural time varying parameter VAR model. Given that there is considerable evidence that the structure of the U.S. economy has changed over the last decades, it is surprising that the empirical literature on technology news shocks has not yet explored whether the size and transmission of such shocks has been stable over time or not. The contribution of this paper is thus novel in this respect.

The TVP-VAR model is developed *inter alia* in Cogley and Sargent (2001) as well as Primiceri (2005) and features both time varying coefficients and stochastic volatility. The model is hence an appropriate framework to address the question of interest since it allows for smooth and permanent changes in the structure of the economy via drifting coefficients, while accounting for the possibility that the size of the shocks is not stable over time. For instance Galí and Gambetti (2009) employ this model to study whether the remarkable decline in the volatility of real activity and inflation since the mid 1980s, known as the *Great Moderation*, was the result of a drop in the magnitude of technology and non-technology shocks. At least in part, they reject this *good luck* hypothesis. Hofmann, Peersman, and Straub (2010) use a structural TVP-VAR model to explore the time variation in the effects of technology surprise shocks on the U.S. economy. Their findings suggest that the high inflation rates of the mid and late 1970s can be linked to a high degree of wage indexation in combination with a weak reaction of the monetary policy authority to inflation. Hofmann et al. (2010) hence provide a richer explanation for the underlying sources of the *Great Inflation* than the well-known *bad luck* story, which suggests that the poor economic performance of the mid and late 1970s was primarily due to exceptionally large unfavorable economic shocks.

The approach of this paper is *structural* in the sense that I work with model-based restrictions in identification. The restrictions are derived from a standard new Keynesian DSGE model and robust to parameter uncertainty. Furthermore, the set of restrictions is sufficient to discriminate technology news shocks from other supply and demand side disturbances, namely technology surprise, monetary policy, preference, and labor supply shocks, respectively. Such a model-based identification strategy is preferable to more conventional short and long-run identification schemes since it neither requires to add an estimate for unobserved technology to the model nor relies on contemporaneous zero restrictions that are often inconsistent with economic theory. Moreover, the methodology used allows me to link the *reduced form* evidence coming from the empirical model to the theoretical business cycle model and hence to provide a possible *structural* explanation for the observed time variation.

Overall, there is little evidence that the variance of technology news shocks or their transmission to real activity and inflation has changed over time. In particular, the findings do not support the hypothesis that such shocks have contributed significantly to the *Great Moderation*. However, I detect significant time variation in the endogenous monetary policy reaction to technology news shocks; responding strongly to inflation most of the time, but less during the *Great Inflation* period. Using the theoretical business cycle model, I argue that the observed time variation in the nominal interest rate may be explained by a systematic change in the relative size of the coefficients in the monetary policy rule before and after the *Great Inflation* period. The evidence of this paper thus supports the hypothesis that the high inflation rates of the mid and late 1970s were the result of *bad policy* rather than *bad luck* as suggested for instance by Clarida, Galí, and Gertler (2000), Cogley and Sargent (2001), or Lubik and Schorfheide (2004).

The remainder of this paper is organized as follows. Section 2 outlines the business cycle model and derives robust theoretical restrictions in order to achieve identification in the empirical model. Section 3 presents the structural TVP-VAR model that is used to explore the time varying transmission of technology news shocks to the U.S. economy. Section 4 documents the time varying impact of technology news shocks on the U.S. economy for the period 1962:4 to 2010:3. The *reduced form* evidence includes the time profiles for impulse responses and the volatility in macroeconomic series that results from these shocks. Section 5 provides a possible *structural* explanation for the reported time variation. Finally, Section 6 concludes.

2 Technology news in a business cycle model

This section outlines the business cycle model and derives robust theoretical restrictions in order to achieve identification in the empirical model. The business cycle model is a closed economy new Keynesian DSGE model,[1] featuring optimizing households and firms, an interest rate setting monetary policy authority, monopolistic competition in the goods market, nominal as well as real rigidities, and five structural shocks, a technology news shock among them. The nominal and real imperfections are included to account for the empirical evidence of staggered price setting, labor market imperfections, and monetary policy non-neutrality. The structural shocks are considered to discriminate technology news from other important supply and demand side disturbances - technology surprise, labor supply, monetary policy, and preference shocks, respectively.

2.1 The model

2.1.1 Households

The model economy is inhabited by a representative infinitely-lived household, seeking to maximize its lifetime utility by choosing purchases of a consumption bundle C_t and one-period bonds B_t, and the labor supply N_t

$$\max E_0 \sum_{t=0}^{\infty} \beta^t e_t^b \left(\frac{C_t^{1-\sigma}}{1-\sigma} - e_t^n \frac{N_t^{1+\varphi}}{1+\varphi} \right), \tag{1}$$

where β is the discount factor, σ denotes the degree of relative risk aversion and φ is the inverse of the labor supply elasticity with respect to the real wage. The household's consumption/savings and labor supply decisions are affected by a preference shock, e_t^b, which alters the intertemporal substitution of the household and a shock to the labor supply, e_t^n. Both shocks are assumed to follow stationary first-order autoregressive processes with i.i.d. innovation terms: $\ln e_t^b = \rho_b \ln e_{t-1}^b + \nu_t^b$ and $\ln e_t^n = \rho_n \ln e_{t-1}^n + \nu_t^n$, where $\ln \cdot$ denotes the natural logarithm.

The maximization of lifetime utility is subject to a sequence of period budget constraints of the following form

$$P_t C_t + Q_t B_t \leq B_{t-1} + W_t N_t + D_t. \tag{2}$$

[1]The model is the standard workhorse in the literature of business cycle analysis. In this paper I use a modified and extended version of the baseline model described in Chapter 3 of Galí (2008).

P_t denotes the aggregate price level, Q_t is the price of a one-period bond, W_t is the nominal wage and D_t is a dividend income from the ownership of firms. The optimal consumption/savings and labor supply plans are characterized by two conditions of the form

$$\frac{W_t}{P_t} = e_t^n N_t^{\varphi} C_t^{\sigma} = MRS_t, \tag{3}$$

$$1 = \beta R_t E_t \left[\frac{e_{t+1}^b}{e_t^b} \frac{C_{t+1}^{-\sigma}}{C_t^{-\sigma}} \frac{P_t}{P_{t+1}} \right], \tag{4}$$

where the latter is a conventional stochastic Euler equation. MRS_t denotes the marginal rate of substitution and $R_t = 1/Q_t$ is the riskless return on a one-period bond paying off one unit of currency in period $t+1$.

In addition to the consumption/savings and labor supply decisions, the household has to decide on the optimal composition of the consumption bundle. Assume the existence of a continuum of goods indexed by $i \in [0,1]$. The consumption bundle is given by

$$C_t = \left[\int_0^1 C_t\left(i\right)^{1-\frac{1}{\epsilon}} di \right]^{\frac{\epsilon}{\epsilon-1}}, \quad \text{for } \epsilon > 1, \tag{5}$$

with $C_t\left(i\right)$ representing the quantity of good i consumed by the household in period t. Maximizing the consumption bundle for any given level of expenditures $\int_0^1 P_t\left(i\right) C_t\left(i\right) di$, yields the following set of demand equations

$$C_t\left(i\right) = \left[\frac{P_t\left(i\right)}{P_t} \right]^{-\epsilon} C_t, \quad \text{for all } i, \tag{6}$$

where $P_t = \left[\int_0^1 P_t\left(i\right)^{1-\epsilon} di \right]^{\frac{1}{1-\epsilon}}$ denotes the aggregate price level, $P_t\left(i\right)$ is the price of good i in period t and ϵ represents the elasticity of good i with respect to its own price.

2.1.2 Firms and price setting

There is a continuum of monopolistically competitive firms indexed by $i \in [0,1]$. Each firm produces a differentiated good using a production function of the form

$$Y_t\left(i\right) = A_t N_t\left(i\right)^{1-\alpha}. \tag{7}$$

A_t is an aggregate technology shock, assumed to be common to all firms and $1-\alpha$ is the steady state labor share of output. Taking the nominal wage W_t and the aggregate price level P_t as given, minimizing total production costs $\frac{W_t}{P_t} N_t\left(i\right)$ with respect to labor input $N_t\left(i\right)$ and subject to the production technology given by Equation (7), yields the following expression for a firm's real marginal costs

$$MC_t(i) = \frac{W_t N_t(i)^{\alpha}}{(1-\alpha) A_t P_t} \ . \tag{8}$$

As in Calvo (1983), firms are not allowed to reset their prices unless they receive a random signal. The probability that a given price can be reoptimized in any particular period is $1-\theta$, independent of the time elapsed since the last adjustment. A firm j reoptimizing in period t chooses the price $P_t^*(j)$ that maximizes the discounted sum of expected nominal profits

$$\max\, E_t \sum_{k=0}^{\infty} \theta^k Q_{t+k} \left[P_t^*(j) Y_{t+k}(j) - P_{t+k} MC_{t+k}(j) Y_{t+k}(j)\right], \tag{9}$$

subject to the sequence of demand functions

$$Y_{t+k}(j) = \left[\frac{P_t^*(j)}{P_{t+k}}\right]^{-\epsilon} C_{t+k}, \qquad \text{for all } \ k, \tag{10}$$

where $Q_{t+k} = \beta^k \left(e_{t+k}^b / e_t^b\right) \left(C_{t+k}/C_t\right)^{-\sigma} \left(P_t/P_{t+k}\right)$ is the stochastic dicount factor of the household owing the firm. The resulting first order condition is

$$E_t \sum_{k=0}^{\infty} \theta^k Q_{t+k} Y_{t+k} \left[P_t^*(j) - (1+\lambda_p) P_{t+k} MC_{t+k}(j)\right] = 0, \tag{11}$$

with $1+\lambda_p = \epsilon/(\epsilon-1)$ denoting the price markup over nominal marginal costs. Under completely flexible prices ($\theta = 0$) and perfectly competitive goods markets ($\lambda_p = 0$), the condition reduces to the familiar $P_t^*(j) = P_t MC_t(j)$.

Since the price setting problem is identical to all firms, each firm i chooses the same price $P_t^*(i) = P_t^*$ when reoptimizing. Hence, the aggregate price level evolves according to the following expression

$$P_t^{1-\epsilon} = \theta P_{t-1}^{1-\epsilon} + (1-\theta)\left(P_t^*\right)^{1-\epsilon}. \tag{12}$$

2.1.3 Monetary policy

The monetary policy authority is assumed to have control over the riskless return, i.e., the nominal short-term interest rate in the economy. In particular, I assume that the interest rate R_t evolves according to the following Taylor-type interest rate rule

$$\frac{R_t}{R_t^{ss}} = \left(\frac{P_t}{P_{t-1}}\right)^{\phi_\pi} \left(\frac{Y_t}{Y_t^f}\right)^{\phi_y} e_t^r, \tag{13}$$

where R_t^{ss} is the steady state interest rate, Y_t^f is the output that would prevail if prices were perfectly flexible, and ϕ_π and ϕ_y represent the elasticity of the interest rate to the quarterly gross inflation rate ($\Pi_t = P_t/P_{t-1}$) and the output gap (Y_t/Y_t^f), respectively. Moreover, deviations from the rule are captured by a monetary policy shock, e_t^r, which follows a stationary first-order autoregressive process with i.i.d. innovation term: ln $e_t^r = \rho_r$ ln $e_{t-1}^r + \nu_t^r$. Once linearized, such a rule is a plausible description of the Fed's policy over the last decades.[2]

2.1.4 Market clearing and real wage rigidities

The model abstracts from capital accumulation, government purchases and net exports. Hence, market clearing in the goods market requires

$$Y_t = C_t, \qquad \text{for all} \;\; t, \tag{14}$$

meaning that aggregate output equals aggregate consumption in equlibrium. Furthermore, the labor market is in equilibrium if the firms' demand for labor equals the labor supply by households at the wage level set by unions.

Similar to Blanchard and Galí (2007, 2009), I introduce real wage rigidities into the model by modifying the household's optimality condition in Equation (3) to

$$\frac{W_t}{P_t} = \left[(1+\lambda_w)\, MRS_t\right]^{1-\gamma}, \tag{15}$$

where $\gamma \in [0,1]$ represents the degree of real wage rigidities in the labor market and $\lambda_w \geq 0$ is a steady state wage markup, chosen to be as large as necessary to prevent the real wage from falling below the marginal rate of substitution at any point in time. Though not explicitly derived from a model of the labor market, Equation (15) is a parsimonious way to capture the notion that labor markets are not perfectly competitive and real wages may adjust only slowly to labor market conditions.[3]

2.1.5 Technology process

In order to explore the response of the model economy to both anticipated and unanticipated changes in aggregate technology, an appropriate process for A_t needs to be specified. Particu-

[2]See for instance Taylor (1993).

[3]The main reason for including labor market imperfections into business cycle models is that more rigid wages translate into more persistent movements of aggregate inflation - a feature often found in the data. See for instance Christoffel, Kuester, and Linzert (2009) or Christoffel and Linzert (2010).

larly, I assume that the technology shock follows a stationary first-order autoregressive process with i.i.d innovation term

$$\ln A_t = \rho_a \ln A_{t-1} + \ln G_{t-1} + \nu_t^a, \tag{16}$$

with G_t itself evolving according to a stationary first-order autoregressive process: $\ln G_t = \rho_g \ln G_{t-1} + \nu_t^g$. To see the implication of this timing assumption, plug the latter expression into Equation (16) and obtain the following process determining the evolution of technology[4]

$$\ln A_t = \rho_a \ln A_{t-1} + \rho_g \ln G_{t-2} + \nu_t^a + \nu_{t-1}^g. \tag{17}$$

Period t changes in aggregate technology are hence the result of either unanticipated innovations, i.e., technology surprise shocks ν_t^a, or due to innovations that are anticipated by economic agents one period in advance, i.e., technology news shocks ν_{t-1}^g.

In an empirical application, however, two difficulties arise. First, technology is not observable. And second, even if data or an estimate for A_t would be available, in a univariate context it is not possible to discriminate between technology surprise and news shocks. To overcome these difficulties, I move beyond univariate time series models and run a vector autoregression on observable variables, not including unobserved or estimated technology. Moreover, I discriminate between technology surprise and news shocks by imposing theoretical restrictions on the short-run response of observable variables. The derivation of these restrictions is outlined in the next section.

2.2 Deriving the sign restrictions

2.2.1 Baseline calibration

In the baseline calibration of the model,[5] I assume that the discount factor $\beta = 0.99$, implying an annual steady state real interest rate of 4%. The Calvo parameter θ determining the degree of nominal rigidites in the goods market is set to 0.75, which implies an average price duration of one year. Following Blanchard and Galí (2009), I target a moderate degree of real wage rigidities ($\gamma = 0.75$) and abstract from any wage markup ($\lambda_w = 0$). The latter assumption does not affect the implications of the model since a positive but constant steady state markup would disappear anyway once the model is simulated in deviations from steady state. Furthermore,

[4]See Barsky and Sims (2011) for a similar approach.

[5]The business cycle model is log-linearized before simulating it. See Appendix A for the linearized equilibrium of the model.

I set the production function parameter $\alpha = 0.33$, consistent with a steady state labor income share of about two third. I also assume that the parameter reflecting the degree of monopolistic competition in the goods market $\epsilon = 6$, equivalent to a price markup over marginal costs of 20% (i.e., $\lambda_p = 0.2$). With respect to the household's preference parameters, I use the following combination. The parameter determining the degree of relative risk aversion σ is set to 3, while the parameter driving the labor supply utility φ is calibrated to 1.5. This parameter choice is equivalent to an intertemporal elasticity of substitution of $1/3$ and a Frisch elasticity of work effort with respect to the real wage of $2/3$. For the parameters of the monetary policy rule, I assume $\phi_\pi = 1.5$ and $\phi_y = 0.5$. Such a parameterization appears to be a plausible description of the Fed's average policy over the last decades. Moreover, a $\phi_\pi > 1$ ensures the determinacy of the model since the monetary policy authority responds to movements in inflation more than just one to one, thus satisfying the *Taylor Principle*. The autoregressive coefficients for the technology surprise, the preference and the labor supply shock are set to $\rho_a = \rho_b = \rho_n = 0.9$, which implies a relatively high degree of persistence for these shocks. Since the persistence of the technology news shock depends on both ρ_a and ρ_g, I use a smaller value for ρ_g compared to ρ_a in order to avoid that the technology news shock becomes *too* persistent. I set $\rho_g = 0.75$. Similarly, I set $\rho_r = 0.75$, consistent with the notion that monetary policy shocks are less persistent than real disturbances. Overall, the parameter constellation used is consistent with a large part of the new Keynesian literature[6] and matches a quarterly model.

Figures 1 and 2 report the results for the technology surprise and news shock, respectively. I show the model implied impulse responses for output (or consumption), inflation, nominal and real interest rates, hours worked, and real wages up to a horizon of 40 quarters after a shock. Both shocks are equal in size (unit innovation) and normalized on a positive output response. Consistent with a large part of the new Keynesian literature, a positive technology surprise shock increases output and real wages, but decreases inflation, nominal as well as real interest rates, and hours worked. Similarly, a positive technology news shock raises output and real wages, while it has a negative impact on inflation. But contrary to the technology surprise shock, the news shock induces a hump-shaped response for output (or consumption) with the maximal effect postponed by several quarters. Given that the increase in income, which comes along with the future technology improvement, is anticipated by foreward-looking households, the postponement of production/consumption may only be explained by a substantial rise in the real interest rate. In fact, the real interest rate displays a positive response to the technology news shock for a few quarters, which separates the technology news from the surprise shock.

[6] See for instance the handbook article by Christiano, Trabandt, and Walentin (2011) for an overview.

Moreover, the technology news shock is associated with a positive response for hours worked and an increase in the nominal interest rate. The latter finding comes from the fact that the technology news shock has a delayed impact on flexible price output and hence leads to a large positive output gap on impact. Given a sufficiently strong reaction of the monetary policy authority to the output gap, the nominal interest rate increases despite the negative response for inflation.

The theoretical impulse responses to the non-technology shocks are shown in Figures 3 to 5. Following a negative monetary policy shock, interest rates, both in nominal and real terms, decline, and output, inflation, hours worked as well as real wages increase. It is this positive correlation between output and inflation that disentangles a monetary policy shock from both technology shocks. The same reasoning applies to the preference shock. In the business cycle model, a preference shock is a standard aggregate demand shock that induces a positive comovement of output, inflation, nominal and real interest rates, hours worked, and real wages. Moreover, the positive correlation between output and inflation on the one hand and real interest rates on the other hand allows me to distinguish preference and monetary policy shocks.

Finally, a negative shock to the labor supply leads to an increase in output and hours worked, but decreases the real wage. The response of the latter discriminates a labor supply from a technology surprise shock. Furthermore, a labor supply shock is different from a technology news shock since it is followed by a negative real interest rate response. In addition, the negative correlation between output and inflation conditional on a labor supply shock separates it from a monetary policy and preference shock.

2.2.2 Simulation exercise

In order to explore the sensitivity of these results with respect to the calibration of the model, I conduct a simulation exercise and exhaust the parameter space by allowing all the structural parameters to vary simultaneously. In particular, I assume that all parameters are uniformly and independently distributed on the intervals reported in Table 1, with prior means equal or close to the values used in the baseline calibration. For the discount factor β, I set the interval to $[0.985, 0.995]$, implying an annual steady state real interest rate between 2% and 6%. Moreover, I restrict the range for both the Calvo parameter θ and the labor market parameter γ to $[0.5, 0.95]$. The interval for the production function parameter α is set to $[0, 0.66]$, which implies a mean steady state labor income share of about two third. I also assume that $\epsilon \in [3, 9]$, meaning that the price markup roughly varies between 10% and 50%. The preference parameters σ and φ are restricted to the intervals $[1, 5]$ and $[0, 3]$, respectively. Moreover, the parameters of the

Table 1: Parameter ranges and values

	Parameter/ description	Simulation	Baseline
β	Discount factor	$[0.985, 0.995]$	0.99
θ	Degree of nominal rigidities in the goods market	$[0.50, 0.95]$	0.75
γ	Degree of real rigidities in the labor market	$[0.50, 0.95]$	0.75
α	Production function parameter	$[0.00, 0.66]$	0.33
ϵ	Degree of monopolistic competition in the goods market	$[3.00, 9.00]$	6.00
σ	Degree of relative risk aversion	$[1.00, 5.00]$	3.00
φ	Inverse of labor supply elasticity	$[0.00, 3.00]$	1.50
ϕ_π	Monetary policy response to inflation	$[1.01, 2.00]$	1.50
ϕ_y	Monetary policy response to output gap	$[0.00, 1.00]$	0.50
ρ_a	Persistence of technology surprise shocks	$[0.75, 0.99]$	0.90
ρ_g	Persistence of technology news shocks	$[0.33, 0.85]$	0.75
ρ_r	Persistence of monetary policy shocks	$[0.33, 0.85]$	0.75
ρ_b	Persistence of preference shocks	$[0.75, 0.99]$	0.90
ρ_n	Persistence of labor supply shocks	$[0.75, 0.99]$	0.90

monetary policy rule are within the ranges typically considered in the literature: $\phi_\pi \in [1.01, 2]$ and $\phi_y \in [0, 1]$. And consistent with the baseline calibration, I target a relatively high degree of persistence for the technology surprise, preference and labor supply shocks and set the corresponding intervals to $[0.75, 0.99]$, while I assume that both ρ_g and ρ_r lie within $[0.33, 0.85]$, hence being less persistent on average.

To obtain a posterior distribution, I repeatedly draw a set of model parameters from these predefined intervals, calculate the associated impulse responses and save them. In total, I perform 10,000 repetitions. The results for this simulation exercise are reported in Figures 6 to 10. Each figure shows the pointwise difference between the 84^{th} and 16^{th} percentiles[7] of the posterior distribution (gray shaded area), hence providing some intuition on the sensitivity of the theoretical impulse responses to the choice of the parameter constellation.

Altogether, the simulation outcome suggests that the results of the previous section are robust to alternative calibrations of the model. With only two exceptions, all impulse responses show the same sign in the short-run compared to the baseline calibration. It turns out that the response for hours worked to a technology surprise shock is particularly sensitive to the parameter choice, which is consistent with the conflicting evidence of the real business cycle and new Keynesian literature in this respect. Moreover, the nominal interest rate may rise or fall

[7]This means that parameter constellations that lead to extreme responses in the tails are ruled out.

Table 2: Theoretical impulse responses

Shock/ variable	Output	Inflation	Real interest rate	Real wages
Technology surprise	$\uparrow$	$\downarrow$	$\downarrow$	$\uparrow$
Technology news	$\uparrow$	$\downarrow$	$\uparrow$	
Monetary policy	$\uparrow$	$\uparrow$	$\downarrow$	
Preference	$\uparrow$	$\uparrow$	$\uparrow$	
Labor supply	$\uparrow$	$\downarrow$	$\downarrow$	$\downarrow$

in response to technology news shocks, depending on the calibration of the model. Given that I need neither the nominal interest rate nor the hours worked to disentangle technology news from other shocks, these findings do not have any consequences for the identification of the empirical model.

Table 2 summarizes the implications derived from the theoretical business cycle model. $\uparrow$ indicates that the model suggests a positive short-run response for a particular variable to a shock, while $\downarrow$ means a negative response. The corresponding entry is left blank if either the theoretical model does not deliver a clear prediction or the restriction is not needed to achieve identification in the empirial model. Hence, this set of restrictions is robust across a wide range of different parameter combinations, while it at the same time respresents the minimum number of restrictions that is needed to discriminate the five shocks.

3 The empirical model

This section presents the structural TVP-VAR model that is used to explore the time varying transmission of technology news shocks to the U.S. economy. The model allows for both time variation in the coefficients and stochastic volatility. With respect to the model specificaton, the calibration of the priors, and the Bayesian estimation procedure, I follow Primiceri (2005). Moreover, I identify technology news shocks per sign restrictions on impulse responses using the theoretical restrictions derived in Section 2.2.

3.1 Bayesian VAR with time varying parameters

Consider the TVP-VAR model

$$y_t = c_t + B_{1,t}y_{t-1} + ... + B_{p,t}y_{t-p} + u_t = X_t' B_t + u_t. \tag{18}$$

y_t is a 5×1 vector of endogenous variables including output growth, inflation, a nominal short-term interest rate, the growth in hours worked, and the growth in real wages in that order; c_t is a 5×1 vector of time varying intercepts; $B_{i,t}$ are 5×5 matrices of time varying coefficients; $i = 1, ..., p$ denotes the lags included; u_t is a 5×1 vector of residual terms with zero mean and time varying covariance matrix Ω_t; and data are available for $t = 1, ..., T$. Let $X_t' = I_5 \otimes \left[1, y_{t-1}', ..., y_{t-p}'\right]$ and $B_t = \text{vec}\left(\left[c_t, B_{1,t}, ..., B_{p,t}\right]'\right)$, where $\otimes$ denotes the Kronecker product and $\text{vec}(\cdot)$ is the column stacking operator, respectively.

The covariance matrix Ω_t can be decomposed as follows[8]

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t', \tag{19}$$

where A_t is a lower triangular matrix which models the contemporaneous interactions among the variables

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix},$$

and Σ_t is a diagonal matrix which contains the stochastic volatilities

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{2,t} & 0 & 0 & 0 \\ 0 & 0 & \sigma_{3,t} & 0 & 0 \\ 0 & 0 & 0 & \sigma_{4,t} & 0 \\ 0 & 0 & 0 & 0 & \sigma_{5,t} \end{bmatrix}.$$

Let α be the vector of non-zero and non-one elements of A_t (stacked by rows), σ_t be the vector of the diagonal elements of Σ_t and B_t be the vector containing all the coefficients of the TVP-VAR. The time varying parameters are assumed to evolve as follows

$$B_t = B_{t-1} + \nu_t, \qquad \nu_t \sim N(0, Q), \tag{20}$$

$$\alpha_t = \alpha_{t-1} + \xi_t, \qquad \xi_t \sim N(0, S), \tag{21}$$

$$\ln \sigma_t = \ln \sigma_{t-1} + \eta_t, \qquad \eta_t \sim N(0, W), \tag{22}$$

[8]This decomposition ensures that the covariance matrix is positive definite.

where the innovation terms have zero mean, are normally distributed and independent of each other. The elements of B_t and A_t are thus modelled as driftless random walks, while the stochastic volatilities in σ_t follow a geometric random walk. The random walk assumption reduces the number of parameters significantly and hence allows for an efficient estimation of the model. To ensure stationarity, I follow Cogley and Sargent (2001) and discard all draws for the coefficient vector that lead to an explosive solution of the TVP-VAR. In particular, I check for each draw whether the roots of the associated TVP-VAR polynomial are outside the unit circle and attribute zero prior weight to it if they are not.

Finally, it is also assumed that S has a block-diagonal structure of the following form:

$$S = \text{Var}\left(\xi_t\right) = \begin{bmatrix} S_1 & 0_{1\times 2} & 0_{1\times 3} & 0_{1\times 4} \\ 0_{2\times 1} & S_2 & 0_{2\times 3} & 0_{2\times 4} \\ 0_{3\times 1} & 0_{3\times 2} & S_3 & 0_{3\times 4} \\ 0_{4\times 1} & 0_{4\times 2} & 0_{4\times 3} & S_4 \end{bmatrix},$$

where $S_1 = \text{Var}\left(\xi_{21,t}\right)$, $S_2 = \text{Var}\left(\left[\xi_{31,t}, \xi_{32,t}\right]'\right)$, $S_3 = \text{Var}\left(\left[\xi_{41,t}, \xi_{42,t}, \xi_{43,t}\right]'\right)$ and $S_4 = \text{Var}\left(\left[\xi_{51,t}, \xi_{52,t}, \xi_{53,t}, \xi_{54,t}\right]'\right)$ with $\text{Var}\left(\cdot\right)$ denoting the variance operator, implying that the coefficients evolve independently in each equation.

3.2 Specifications and data

I use quarterly U.S. data running from 1947:1 to 2010:3, obtained from the Federal Reserve Economic Data (FRED) database.[9] For output growth I include the (log) change in real GDP (GDPC1), for inflation the (log) change in the GDP deflator (GDPDEF), for the nominal short-term interest rate a 3-month Treasury bill rate (TB3MS), for growth in hours worked the (log) change in total hours worked in the nonfarm business sector (HOANBS) and for growth in real wages the (log) change in real compensation per hour in the nonfarm business sector (COMPRNBF). The mnemonics used by FRED are in parantheses.

Furthermore, I construct the impulse response for the real interest rate by taking the difference between the response for the nominal interest rate and the TVP-VAR model implied one-quarter ahead forecast for inflation.[10] Finally, I set the lag length to $p = 2$. Given that the series included are stationary, such a parsimonious order should be sufficient to capture the dynamics in the system, while it also keeps the estimation procedure tractable.

[9] See also Appendix B.

[10] For this reason I use a 3-month rate rather than the federal funds rate to measure monetary policy.

3.3 Priors and estimation

The TVP-VAR model is estimated using Bayesian methods. In order to calibrate the prior distributions for the initial states, I run a constant parameter version of the model on a small training sample from 1947:2 to 1962:1 using ordinary least squares (OLS). The remaining data from 1962:2 to 2010:3 are used to estimate the model. Following Primiceri (2005), I assume that the initial states for the coefficients (B_0), the contemporaneous relations (A_0), the stochastic volatilities (σ_0) and the hyperparamters (Q, S, W) are independent of each other. Let $\hat{x}$ denote the OLS point estimate for a parameter x and $\hat{V}_{\hat{x}}$ the corresponding variance. For the coefficients and contemporaneous relations I specify normal priors $p(\cdot)$ of the following form: $p(B_0) = N\left(\hat{B}, 4 \cdot \hat{V}_{\hat{B}}\right)$ and $p(A_0) = N\left(\hat{A}, 4 \cdot \hat{V}_{\hat{A}}\right)$, where the mean values of B_0 and A_0 are set to their OLS point estimates, and the variances are chosen to be four times their variances in a constant parameter version of the model. Moreover, I assume a log-normal prior for the stochastic volatilities: $p(\ln \sigma_0) = N(\ln \hat{\sigma}, I_5)$. I set the mean value for σ_0 to the corresponding OLS point estimate and the variance to the identity matrix.[11]

Let $IW(\Psi, m)$ denote the inverted Wishart distribution with scale matrix Ψ and m degrees of freedom. The priors for the hyperparameters Q and W are specified as follows: $p(Q) = IW\left(0.0001 \cdot 60 \cdot \hat{V}_{\hat{B}}, 60\right)$ and $p(W) = IW(0.0001 \cdot 6 \cdot I_5, 6)$, where the scale matrices are constant fractions of the variances from a time invariant model (multiplied by the degrees of freedom), while the degrees of freedom are set to the size of the training sample (60 observations) and to one plus the dimension of the σ_0 matrix ($1 + \dim(\sigma_0) = 6$), respectively. Finally, I use the following priors for the blocks of S: $p(S_1) = IW\left(0.01 \cdot 2 \cdot \hat{V}_{\hat{A}_1}, 2\right)$, $p(S_2) = IW\left(0.01 \cdot 3 \cdot \hat{V}_{\hat{A}_2}, 3\right)$, $p(S_3) = IW\left(0.01 \cdot 4 \cdot \hat{V}_{\hat{A}_3}, 4\right)$ and $p(S_4) = IW\left(0.01 \cdot 5 \cdot \hat{V}_{\hat{A}_4}, 5\right)$, where $\hat{A}_1, \hat{A}_2, \hat{A}_3$ and $\hat{A}_4$ are the corresponding blocks to S_1, S_2, S_3 and S_4 of $\hat{A}$. The degrees of freedom are set to one plus the number of corresponding entries in α_0. Specified in this way, the prior is diffuse and uninformative, and soon dominated by the information in the data.

To simulate the joint posterior distribution of ($B^T, A^T, \Sigma^T, Q, S, W$), I use a Gibbs sampling algorithm.[12] The Gibbs sampler is a Markov chain Monte Carlo (MCMC) method and is carried out by sequentially drawing time varying coefficients (B^T), contemporaneous relations (A^T), stochastic volatilities (Σ^T) and hyperparamters (Q, S, W), given the data and the rest of the parameters. The approach allows for an efficient estimation of the model since it treats all parameters as separate blocks in a Gibbs sampling algorithm and does not require to write down

[11] Flatter specifications of these priors produce similar results.

[12] The Gibbs sampling algorithm is outlined in Appendix C.

a complicated likelihood for the model. The superscript $(\cdot)^T$ indicates that the complete data is used in estimation. The Gibbs sampler thus produces smoothed estimates of the parameters using all the information availale in the data, as opposed to filtered estimates that exhaust only the information contained in a particular subsample.

In total, I perform 20,000 iterations[13] of the Gibbs sampler, discarding the first 15,000 to abstract from the diffuse prior and only keep every 10^{th} of the remaining 5,000 draws to break the autocorrelation among them. Since the Gibbs sampler is a dependence chain algorithm, posterior draws are not independent of each other. The remaining 500 draws are used for structural analysis.

3.4 Identification

Consider the following structural representation of the TVP-VAR model in Equation (18):

$$y_t = X_t' B_t + \Xi_t \epsilon_t, \qquad E\left[\epsilon_t \epsilon_t'\right] = I_5, \tag{23}$$

where Ξ_t maps the five structural shocks (ϵ_t) into the residual terms (u_t). If Ξ_t contains at least $\frac{5(5-1)}{2} = 10$ restrictions for any $t = 1, ..., T$, the system is just identified. A possible candidate for Ξ_t is the lower triangular Cholesky factor of Ω_t such that $\Xi_t \Xi_t' = \Omega_t$. Observe that, if there exists a 5×5 orthonormal matrix H such that $HH' = I_5$, $\Xi_t H$ is also a possible decomposition, associated with a different impulse matrix $\Xi_t H \epsilon_t$. This ability to create a large number of candidate impulse matrices is the basis for the sign restriction approach.[14]

To obtain technology news shocks, I use the following algorithm. First, I estimate the TVP-VAR as described in the previous section and sample 500 representative (non-explosive) states of the economy for each point in time. Second, for each draw I construct 500 candidate impulse matrices by randomly drawing orthonormal matrices using the multiple of the basic set of Givens matrices.[15] Third, I check for each cycle whether the candidate impulse matrix delivers responses that have the following characteristics. The technology news shock increases output and the real interest rate, but decreases inflation. These restrictions are imposed at horizons 0

[13]Further increasing the number of iterations delivers similar results.

[14]There exists an extensive literature on the working of the sign restriction approach. See for instance Canova and De Nicoló (2002) or Uhlig (2005) for further details. Dedola and Neri (2007) as well as Peersman and Straub (2009) are among the first who consider sign restrictions that are explicitly derived from theoretical business cycle models.

[15]The construction of the rotation matrices is explained in Appendix D.

to 3 as ≥ 0 or ≤ 0, which is in line with the predictions of the business cycle model.[16] I keep the candidate draw if all the restrictions are satisfied, otherwise I discard it. This procedure leaves me with roughly 6,000-14,000 responses for each point in time which I use for inference. Since the focus of the empirical analysis is on technology news shocks, I do not attempt to identify the other four shocks in the system.[17]

4 Time varying impact of technology news shocks

This section documents the time varying impact of technology news shocks on the U.S. economy for the period 1962:4 to 2010:3. I report the time profiles for impulse responses and the volatility in macroeconomic series that results from the shocks. The *reduced form* evidence provided in this section is followed by Section 5 which outlines a possible *structural* explanation for the reported time variation.

4.1 Time varying impulse responses

Figures 11 to 16 report the time varying impulse responses to technology news shocks for output growth, inflation, the nominal interest rate, the real interest rate, the growth in hours worked, and the growth in real wages, respectively. Each three-dimensional (3D) graph shows the posterior mean[18] at horizons 0 to 20 for the time period from 1962:4 to 2010:3. The x-axis plots the horizon in quarters, the y-axis denotes the time period, and the z-axis shows the response in percent or percentage points. Except for inflation and the nominal interest rate, I reverse the ordering of the x-axis for better visibility.

As Figure 11 shows, there is little time variation in the response of output growth to technology news shocks. Output growth increases contemporaneously by about 1% on average and

[16]In fact, the restriction on the real interest rate is stronger than implied by the theoretical model. However, as Canova and Paustian (2010) show, for the sign restriction approach to work properly, a sufficiently large number of restrictions is needed. The one-year horizon chosen for the sign restrictions seems to be reasonable in this respect, while the link between the theoretical model and the empirical analysis remains close. For the limitations of the sign restriction approach, see also Fry and Pagan (2010).

[17]The set of theoretical restrictions derived in the previous section could be used to identify technology news, technology surprise, monetary policy, preference, and labor supply shocks simultaneously, and hence to achieve a full identification of the TVP-VAR. However, I repeat the estimation and identification procedure for each quarter between 1962:4 and 2010:3, i.e., 192 times, implying that achieving even partial identification is cumbersome.

[18]The posterior mean is similar to the median but comes with smaller computational costs since it does not require to save the complete posterior distribution for each response.

declines thereafter. However, the impulse responses display a substantial degree of persistence; it takes roughly 8-12 quarters for output growth to return to its pre-shock level. This in fact implies a hump-shaped response for the *level* of output with the maximal effect postponed by about 2-3 years, which is in line with the predictions of the business cycle model.[19] Though the persistence of the responses seems to be larger in some periods than in others, I do not obtain any evidence in favor of a *systematic* change in the impact of technology news shocks on output growth. The same conclusion can be drawn for the impact on inflation that is shown in Figure 12. There is no evidence that the shape of impulse responses varies systematically over time. By construction, inflation is negative on impact and in the three following quarters. The initial decline is estimated to be around 1.2% and shows little variation across time periods. Furthermore, the deflationary effect of technology news shocks goes well beyond the first year after the shock. Across time periods inflation needs around 2-3 years to return to its pre-shock level, but without showing a systematic change towards a more or less persistent behavior over time.

The picture is, however, different in case of the nominal interest rate for which the impulse responses in Figure 13 exhibit substantial time variation. The first part of the sample, running from the early 1960s to the early 1970s, is associated with an immediate - and in some years strong - decline in the nominal interest rate. Around the mid 1970s though, the response for the nominal interest rate switches its sign for several years, before again showing a negative sign for most of the years from the mid 1980s onwards. Given that both the sign and magnitude of the initial responses for output growth and inflation are relatively stable over time, a possible explanation for the observed time variation in the nominal interest rate is a change in the systematic component of the monetary policy rule, responding strongly to inflation most of the time but less during the high inflation period of the mid and late 1970s - the *Great Inflation* era.[20] As is shown in Section 2, the sign of the response for the nominal interest rate in the business cycle model is not robust to parameter uncertainty, depending, among others, on the calibration of the coefficients in the monetary policy rule. I return to this issue in the context of the structural analysis in the next section. In addition, the real interest rate in Figure 14 displays a similar response to the technology news shocks across time periods (around 2.5% on impact) with the exception of the mid and late 1970s when the response is both stronger (up to 3.5%

[19]Remember that the identification restrictions are imposed on the level of output, i.e., the cumulated impulse responses, not on growth rates, meaning that a negative response for output growth from horizon 1 onwards is not *a priori* ruled out.

[20]In the business cycle model, the nominal interest rate adjusts to changes in inflation and the output gap, not output growth. However, in the initial period after a technology news shock, output growth and output gap coincide since flexible price output responds with a delay only.

on impact) and more volatile, also supporting the view that a different monetary policy regime was operating during that period.

Figures 15 and 16 plot the responses for the growth in hours worked and real wages, respectively. Conditional on technology news shocks, the growth in hours worked increases on impact by about 0.8% and declines in the quarters that follow. The shape of the impulse responses is similar across periods and exhibits a substantial degree of persistence. The growth in hours worked returns to its pre-shock level not before 8-12 quarters after a shock. The growth in real wages, however, is less persistent; most of the adjustment - meaning the rise in real wages in response to the expected increase in aggregate technology - takes place within a few quarters. Such a rapid pass-through of technology news shocks to real wages is presumably the result of an only moderate degree of labor market rigidities. Moreover, the contemporaneous response of real wage growth is stable over time (about 1.5% on impact), thus providing no posterior support for structural changes in the U.S. labor market during the Post-World War II period.

Given that the 3D graphs shown do not account for the uncertainty surrounding the impulse responses, I provide additional evidence on the posterior uncertainty in Figures 17, which plots the posterior mean responses for the initial quarter after the shock together with a 68 percent confidence interval.[21] With respect to output growth, inflation, the growth in hours worked and real wages, Figure 17 underlines the previous findings. There is little time variation in the inital responses of these variables to technology news shocks. Moreover, the width of the confidence intervals is similar across time periods, not supporting the hypothesis that the size of the shocks or their transmission to real activity and inflation has changed over time.

In contrast, the nominal interest rate shows significant variation across time periods. The initial response is negative during the 1960s, switches its sign in the mid 1970s, and is again negative for most time periods from the mid 1980s onwards. What is even more important, the sign switch in the mid 1970s is significant in the sense that the complete posterior confidence interval shifts upwards around that date. The endogenous monetary policy response to technology news shocks is hence *a posteriori* different during the mid and late 1970s compared to the periods before and after. This conclusion also emerges from the initial response of the real interest rate which is rather stable over time but exhibits several spikes during the 1970s and early 1980s, both in the mean and bounds of the posterior confidence interval.

[21]The 68 percent confidence interval is calculated as the pointwise difference between the 84^{th} and 16^{th} percentiles of the posterior distribution and corresponds to a one standard error band under normality.

4.2 Evolution of the volatility

Before providing a possible structural explanation for the observed time variation in the monetary policy response to technology news shocks in the next section, I show the posterior distribution of the volatility in macroeconomic series that results from the shocks. I measure volatility by the variance in the series that would prevail if technology news shocks were the only structural disturbances in the economy, i.e., the sum of squared impulse responses. Figure 18 shows the posterior median variance together with a 68 percent confidence interval for output growth, inflation, nominal and real interest rates, as well as the growth in hours worked and real wages for the time period from 1962:4 to 2010:3.

The following findings are worth noting. First, the contribution of technology news shocks to the variance of output growth, inflation, hours worked and real wage growth is relatively stable across time periods, showing no tendency to decline as suggested by the *Great Moderation* hypothesis. Moreover, the confidence intervals also exhibit no systematic change over time, being roughly of the same width on average. Thus, there is no posterior evidence that technology news shocks have contributed significantly to the *Great Moderation*, i.e., the remarkable decline in the volatility of real activity and inflation since the mid 1980s. Second, the volatility in the nominal interest rate due to technology news shocks is also rather stable over time, except for the late 1960s and in particular the early 1980s when Paul Volcker became chairman of the Fed. For the real interest rate, volatility spikes are concentrated on the 1970s and early 1980s, while the periods before and after show little time variation.

5 Explaining the evidence

Comparing impulse responses and volatilities across time periods is potentially problematic since it is not possible to exactly disentangle to what extent the observed time variation is due to changes in the size of the shocks or the transmission mechanism, i.e., the underlying structure of the economy. For each variable, the initial response is always a combination of both. Hence, if we observe that the response of the nominal interest rate is larger in a given period than before, it is not a priori clear whether this is due to the fact that the size of the technology news shocks has increased or the structure of the economy changed. In order to overcome this problem, part of the related literature proposes to normalize on the initial response of a particular variable and interprets the resulting impulse responses as being generated by shocks of equal size.[22]

[22] See for instance Canova, Gambetti, and Pappa (2007) or Gambetti, Pappa, and Canova (2008) who normalize on output growth (demand shocks), inflation (supply shocks) and the nominal interest rate

Given that any normalization scheme is to some extent arbitrary, however, I do not follow this avenue but nevertheless provide a possible - and plausible - interpretation of the observed time variation in the nominal interest rate.

Recall that neither output growth nor inflation show significant variation in the response to technology news shocks over time, while the nominal interest rate does. Thus, if the time variation in the nominal interest rate would have been the result of shocks of different size, the structure of the economy must have always changed in such a way that the impact on output growth and inflation does not change. Such a behavior of the economy seems, however, unlikely. What appears more plausible though is that the constant response of output growth and inflation to technology news shocks reflects the fact that the shocks are similar in size across periods and the time variation in the nominal interest rate is instead due to systematic changes in the endogenous component of the monetary policy rule.

To support this hypothesis, consider Figure 19, which shows the impulse responses for output growth, inflation, and the nominal interest rate at four selected dates: 1967:4, 1976:4, 1992:4, and 2008:4. These dates are chosen to represent in turn the period prior to the build up in inflation, the *Great Inflation* period, the *Great Moderation* period, and finally the recent *Great Recession* period.[23] The graphs report the posterior mean together with a 68 percent confidence interval. Across these *Great Events*, the impulse responses for output growth and inflation exhibit a similar pattern. For the nominal interest rate, the impulse responses are also similar across time, except for the *Great Inflation* period. Around 1976:4, the response significantly switches its sign from negative to positive, which can hardly be the result of a change in the magnitude of the technology news shocks, given the constant output growth and inflation responses. The theoretical business cycle model suggests, however, that the monetary policy reaction to technology news shocks crucially depends on the coefficients in the interest rate rule, i.e., the elasticity of the nominal interest rate with respect to inflation (ϕ_π) and the output gap (ϕ_y), respectively. The sign switch during the *Great Inflation* period may thus be explained by a decline in ϕ_π relative to ϕ_y, probably reflecting a change in the central bank's preferences towards a larger weight on output gap stabilization relative to stabilizing the rate of inflation.

In order to illustrate this point, I simulate the business cycle model for two different monetary policy regimes. First, I include an interest rate rule with an exceptionally weak response to inflation ($\phi_\pi = 1.01$) and a strong response to the output gap ($\phi_y = 0.9$), mimicking the per-

(monetary policy shocks), respectively. Canova and Gambetti (2009) also normalize on the nominal interest rate in the context of monetary policy shocks.

[23]Choosing different quarters in the proximity of the selected dates gives a similar picture.

ceived monetary policy reaction during the *Great Inflation* era. Second, I consider a less accommodative rule with a weak response to the output gap ($\phi_y = 0.1$) but a strong one to inflation ($\phi_\pi = 2$). The latter rule should capture monetary policy behavior before and after the high inflation period of the mid and late 1970s. All remaining structural parameters are set to their values in the baseline calibration.

The theoretical impulse responses for output, inflation, and the nominal interest rate under both regimes are shown in Figure 20. Under the accommodative monetary policy regime, the nominal interest rate increases in response to the expansionary technology news shock despite the decline in inflation (see left panel). Shifting monetary policy towards a more aggressive reaction to inflation and a less accommodative one to the output gap induces an immediate decline in the nominal interest rate (see right panel). Hence, a systematic change in the relative size of ϕ_π and ϕ_y before and after the *Great Inflation* period is a possible - and plausible - explanation for the observed time variation in the nominal interest rate.

6 Conclusion

This paper examines the time varying impact of technology news shocks on the U.S. economy during the Post-World War II era using a structural time varying parameter VAR model. The TVP-VAR is developed *inter alia* in Cogley and Sargent (2001) as well as Primiceri (2005) and allows for both time varying coefficients and stochastic volatility. Recent applications to the transmission of technology surprise shocks to the U.S. economy include Galí and Gambetti (2009) as well as Hofmann et al. (2010). In order to analyze the time varying effects of U.S. monetary policy, the model is used in Canova and Gambetti (2009) and Baumeister and Benati (2010), while Pereira and Lopes (2010) and Kirchner, Cimadomo, and Hauptmeier (2010) provide an application to U.S. and euro area fiscal policy, respectively. Moreover, Baumeister and Peersman (2008) investigate the time varying impact of oil supply shocks on the U.S. economy within the same framework. An application to technology news shocks is, however, not yet available.

In identification I work with model-based restrictions for two reasons. First, the contemporaneous zero restrictions frequently used are often absent in theoretical business cycle models and thus hard to defend. Second, the model-based approach allows me to link the *reduced form* evidence coming from the TVP-VAR to the business cycle model and hence to provide a possible - and plausible - *structural* explanation for the observed time variation. The identification restrictions are derived from a standard new Keynesian DSGE model and hold for a wide range of parameter constellations. Moreover, the set of restrictions is sufficient to discriminate technology news shocks from other supply and demand side disturbances.

Overall, there is little evidence that the variance of technology news shocks or their transmission to real activity and inflation has changed over time. In particular, the findings do not support the hypothesis that such shocks have contributed significantly to the *Great Moderation*. However, I detect significant time variation in the endogenous monetary policy reaction to technology news shocks; responding strongly to inflation most of the time, but less during the *Great Inflation* period. Using the theoretical business cycle model, I argue that the observed time variation in the nominal interest rate may be explained by a systematic change in the relative size of the coefficients in the monetary policy rule before and after the *Great Inflation* period.

The evidence of this paper thus supports the hypothesis that the high inflation rates of the mid and late 1970s were the result of *bad policy* rather than *bad luck* as suggested for instance by Clarida et al. (2000), Cogley and Sargent (2001), or Lubik and Schorfheide (2004). However, I cannot rule out that besides this systematic change towards a less aggressive monetary policy stance on inflation during the 1970s, other factors, such as larger *exogenous* monetary policy or technology surprise shocks, have also contributed to the build up in inflation (see, e.g., Sims and Zha, 2006; Canova and Gambetti, 2009, among others). The findings of this paper are hence not necessarily inconsistent with the *bad luck* story.

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A The linearized business cycle model

The following equations summarize the log-linearized equilibrium of the model. All variables are expressed in percentage deviation from steady state.

$$\hat{c}_t = E_t \hat{c}_{t+1} - \frac{1}{\sigma}\left(\hat{r}_t - E_t \hat{\pi}_{t+1}\right) + \frac{1}{\sigma}\left(\hat{e}_t^b - E_t \hat{e}_{t+1}^b\right) \tag{A.1}$$

$$\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} + \frac{(1-\theta)(1-\beta\theta)}{\theta} \frac{1-\alpha}{1-\alpha+\alpha\epsilon} \hat{mc}_t \tag{A.2}$$

$$\hat{mc}_t = (\hat{w}_t - \hat{p}_t) - \hat{a}_t + \alpha \hat{n}_t \tag{A.3}$$

$$(\hat{w}_t - \hat{p}_t) = (1-\gamma)\left(\hat{e}_t^n + \varphi \hat{n}_t + \sigma \hat{c}_t\right) \tag{A.4}$$

$$\hat{y}_t = \hat{a}_t + (1-\alpha)\hat{n}_t \tag{A.5}$$

$$\hat{y}_t = \hat{c}_t \tag{A.6}$$

$$\hat{r}_t = \phi_\pi \hat{\pi}_t + \phi_y\left(\hat{y}_t - \hat{y}_t^f\right) + \hat{e}_t^r \tag{A.7}$$

$$\hat{y}_t^f = \frac{1+(1-\gamma)\varphi}{(1-\alpha)(1-\gamma)\sigma + (1-\gamma)\varphi + \alpha} \hat{a}_t - \frac{(1-\alpha)(1-\gamma)}{(1-\alpha)(1-\gamma)\sigma + (1-\gamma)\varphi + \alpha} \hat{e}_t^n \tag{A.8}$$

The equations are in that order: the consumption Euler equation, the inflation equation or new Keynesian Phillips curve with inflation driven by marginal costs, marginal costs, the labor supply curve with real wage rigidities, the production function, the goods market clearing condition, the interest rate rule, and the equation characterizing flexible price output.

B The data

The quarterly U.S. data are from the Federal Reserve Economic Data (FRED) database and cover the period 1947:1 to 2010:3.

Real Gross Domestic Product (GDPC1), billions of chained 2005 dollars, sa
Gross Domestic Product: Implicit Price Deflator (GDPDEF), index 2005 = 100, sa
3-Month Treasury Bill: Secondary Market Rate (TB3MS), Percent
Nonfarm Business Sector: Hours of All Persons (HOANBS), index 2005 = 100, sa
Nonfarm Business Sector: Real Compensation per Hour (COMPRNBF), index 2005 = 100, sa

sa: seasonally adjusted; FRED mnemonics in parantheses

C The Gibbs sampling algorithm

This appendix sketches the Gibbs sampling algorithm used to estimate the TVP-VAR. See Primiceri (2005), Carter and Kohn (1994), Gelman, Carlin, Stern, and Rubin (1995), as well as Kim, Shepard, and Chib (1998) for further details.

Step 1: Initialize A^T, Σ^T, s^T, Q, S, and W.

Step 2: Sample B^T from $p\left(B^T|Y^T, A^T, \Sigma^T, Q, S, W\right)$.

Conditional on all other parameters and the data, the observation equation $y_t = X_t' B_t + u_t = X_t' B_t + A_t^{-1}\Sigma_t e_t$, with $e_t \sim N(0, I)$, is linear and has Gaussian innovations. Draws for $B_t = B_{t-1} + \nu_t$ are obtained from $N\left(B_{t|t+1}, P_{t|t+1}\right)$, where $B_{t|t+1} = E\left(B_t|B_{t+1}, Y^T, A^T, \Sigma^T, Q, S, W\right)$ and $P_{t|t+1} = \text{Var}\left(B_t|B_{t+1}, Y^T, A^T, \Sigma^T, Q, S, W\right)$, using the algorithm of Carter and Kohn (1994).

Step 3: Sample A^T from $p\left(A^T|Y^T, B^T, \Sigma^T, Q, S, W\right)$.

The system of equations $y_t = X_t' B_t + A_t^{-1}\Sigma_t e_t$ can be written as $A_t\left(y_t - X_t' B_t\right) = A_t \hat{y}_t = \Sigma_t e_t$, where, conditional on B^T, $\hat{y}_t$ is observable. Since A_t is lower triangular with ones on the main diagonal, the system of equations is given by

$$\hat{y}_{1,t} = \sigma_{1,t} e_{1,t}, \tag{C.1}$$

$$\hat{y}_{i,t} = -\hat{y}_{[1,i-1],t}\alpha_{i,t} + \sigma_{i,t} e_{i,t}, \quad i = 2, ..., 5\ , \tag{C.2}$$

where $e_{i,t}$ is the i-th element of e_t and $\hat{y}_{[1,i-1],t}$ denotes the row vector $[\hat{y}_{1,t}, \hat{y}_{2,t}, ..., \hat{y}_{i,t}]$. Given that S is block-diagonal, the algorithm of Carter and Kohn (1994) can be applied equation by equation to obtain draws for $\alpha_{i,t}$ from $N\left(\alpha_{i,t|t+1}, \Lambda_{i,t|t+1}\right)$, where $\alpha_{i,t|t+1} = E\left(\alpha_{i,t}|\alpha_{i,t+1}, Y^T, B^T, \Sigma^T, Q, S, W\right)$ and $\Lambda_{i,t|t+1} = \text{Var}\left(\alpha_{i,t}|\alpha_{i,t+1}, Y^T, B^T, \Sigma^T, Q, S, W\right)$.

Step 4: Sample Σ^T from $p\left(\Sigma^T|Y^T, A^T, B^T, Q, S, W, s^T\right)$.

Consider the system of non-linear measurement equations $A_t\left(y_t - X_t' B_t\right) = y_t^* = \Sigma_t e_t$, where, conditional on B^T and A^T, y_t^* is observable. Squaring and taking logarithms of each element converts the system into a linear one:

$$y_t^{**} = 2\ h_t + g_t, \tag{C.3}$$

$$h_t = h_{t-1} + \eta_t, \tag{C.4}$$

where $y_{i,t}^{**} = \ln\left[\left(y_{i,t}^{*}\right)^2 + 0.001\right]$; the constant (0.001) makes the estimation procedure more robust; $h_{i,t} = \ln\ \sigma_{i,t}$; and $g_{i,t} = \ln\left(e_{i,t}^2\right)$. Though linear, the system is non-Gaussian since the innovations in the measurement equations are distributed as $\ln\chi^2\,(1)$. I follow Kim et al. (1998) and use a mixture of seven normal densities with component probabilities q_j, means $m_j - 1.2704$, and variances v_j^2 to transform the system into a Gaussian one. The parameters $\left(q_j, m_j, v_j^2\right)$ are chosen to match the moments of the ln $\chi^2\,(1)$ distribution:

Table 3: Mixing distributions as in Kim et al. (1998)

j	q_j	m_j	v_j^2
1	0.00730	-10.12999	5.79596
2	0.10556	-3.97281	2.61369
3	0.00002	-8.56686	5.17950
4	0.04395	2.77786	0.16735
5	0.34001	0.61942	0.64009
6	0.24566	1.79518	0.34023
7	0.25750	-1.08819	1.26261

Let $s^T = [s_1, ..., s_T]'$ be the matrix of indicator variables selecting the member of the mixture, $j = 1, ..., 7$, used for each element of e. Conditional on B^T, A^T, Q, S, W, and s^T, the system is approximately Gaussian and the algorithm of Carter and Kohn (1994) can be used to draw h_t from $N\left(h_{t|t+1}, H_{t|t+1}\right)$, where $h_{t|t+1} = E\left(h_t|h_{t+1}, Y^T, A^T, B^T, Q, S, W, s^T\right)$ and $H_{t|t+1} = \text{Var}\left(h_t|h_{t+1}, Y^T, A^T, B^T, Q, S, W, s^T\right)$.

Step 5: Sample Q, S, W from $p\left(Q|Y^T, A^T, B^T, \Sigma^T\right)$, $p\left(S|Y^T, A^T, B^T, \Sigma^T\right)$, and $p\left(W|Y^T, A^T, B^T, \Sigma^T\right)$, respectively.

Conditional on Y^T, A^T, B^T, and Σ^T, the hyperparameters Q, S, W have inverse-Wishard posterior distributions from which draws can be directly obtained, see Gelman et al. (1995).

Step 6: Go to step 2.

D Rotation matrices

In the context of a five variable VAR a 5×5 Givens matrix has, for example, the following form

$$H_{3,4}(\theta_8) = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \cos(\theta_8) & -\sin(\theta_8) & 0 \\ 0 & 0 & \sin(\theta_8) & \cos(\theta_8) & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix},$$

i.e., the matrix is the 5×5 identity matrix in which the (3,4) and (4,3) elements are replaced by the sine terms and the angle θ_8 lies within $[0, \pi]$. Accordingly, I replace the (3,3) and (4,4) elements by the cosine terms. To construct an orthonormal matrix H, I use the multiple of the basic set of Givens matrices: $H = H_{1,2}(\theta_1) \times H_{1,3}(\theta_2) \times H_{1,4}(\theta_3) \times H_{1,5}(\theta_4) \times H_{2,3}(\theta_5) \times H_{2,4}(\theta_6) \times H_{2,5}(\theta_7) \times H_{3,4}(\theta_8) \times H_{3,5}(\theta_9) \times H_{4,5}(\theta_{10})$. The angles θ_i are randomly drawn from a uniform distribution on $[0, \pi]$.

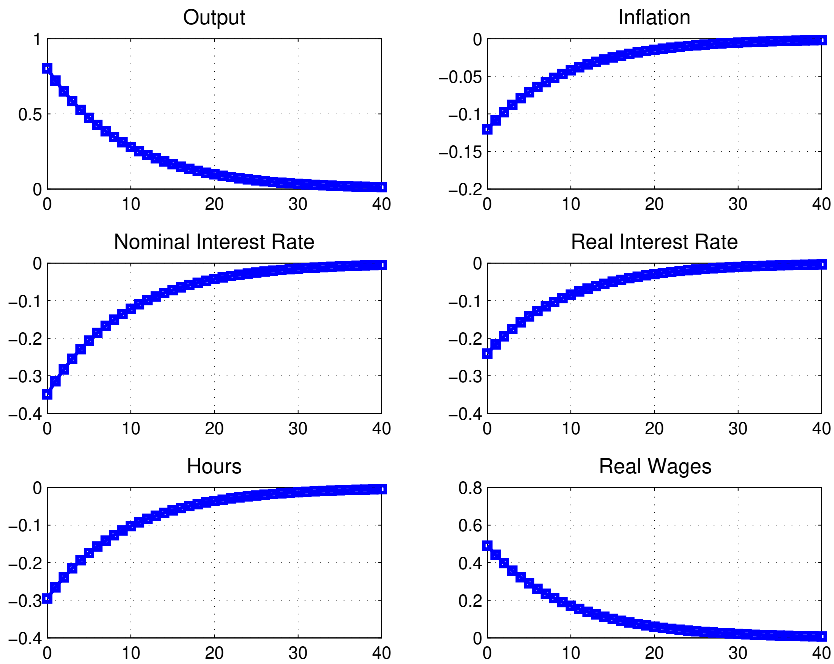

Figure 1: Theoretical impulse responses to a technology surprise shock: Baseline calibration. Note: x-axis: quarters; y-axis: percentage deviation from steady state.

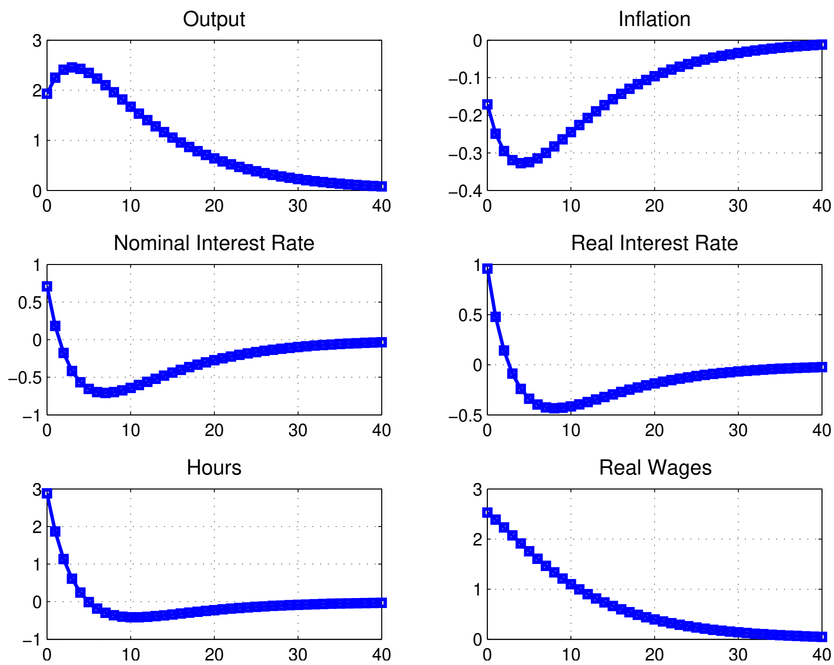

Figure 2: Theoretical impulse responses to a technology news shock: Baseline calibration. Note: x-axis: quarters; y-axis: percentage deviation from steady state.

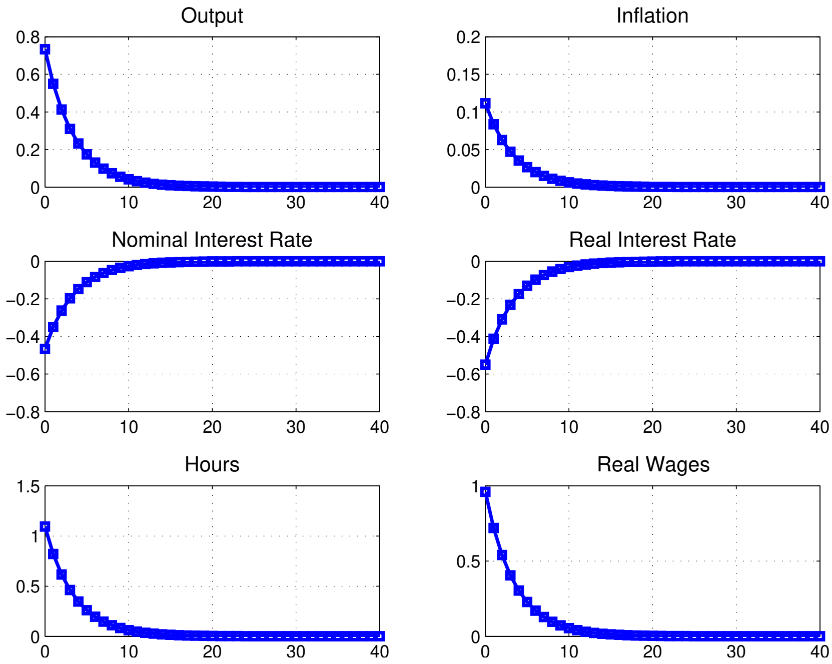

Figure 3: Theoretical impulse responses to a monetary policy shock: Baseline calibration. Note: x-axis: quarters; y-axis: percentage deviation from steady state.

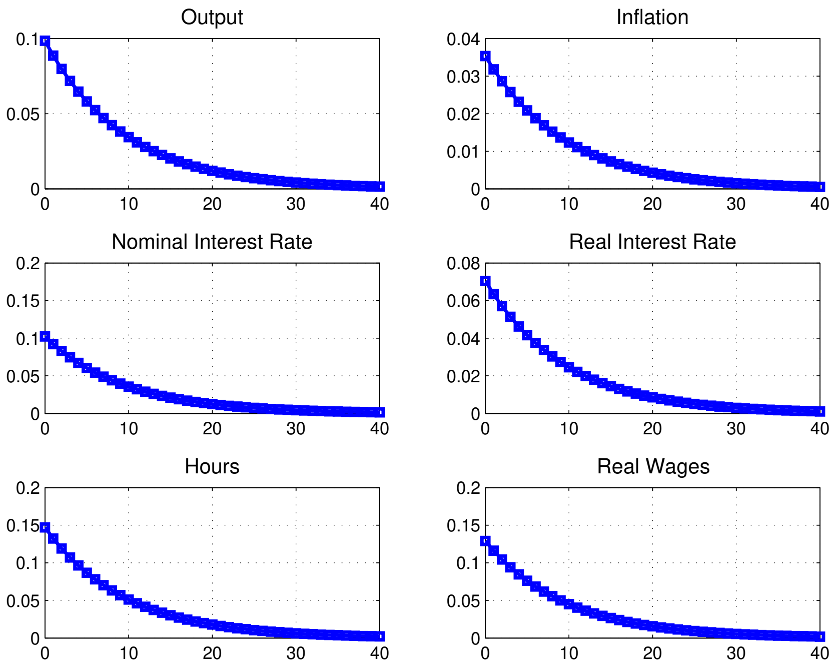

Figure 4: Theoretical impulse responses to a preference shock: Baseline calibration. Note: x-axis: quarters; y-axis: percentage deviation from steady state.

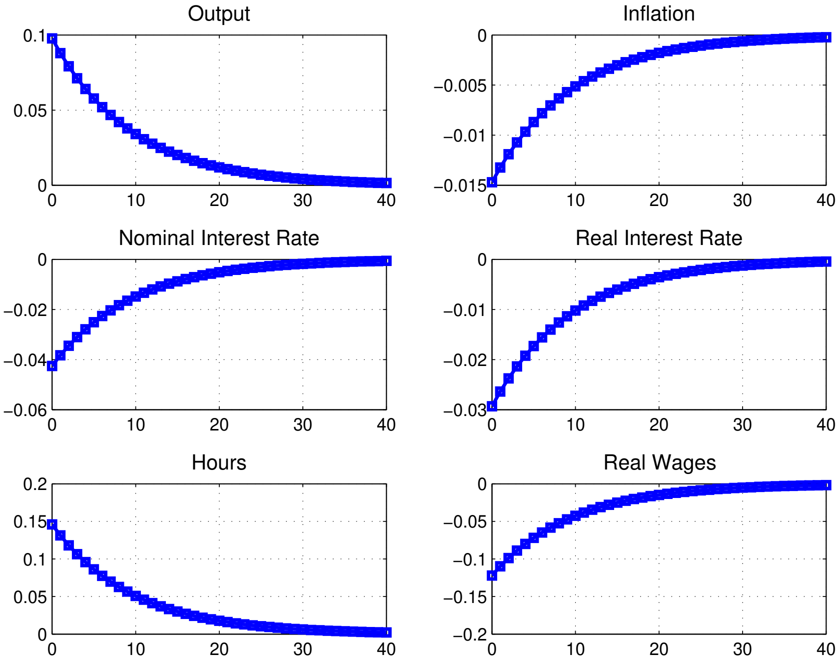

Figure 5: Theoretical impulse responses to a labor supply shock: Baseline calibration. Note: x-axis: quarters; y-axis: percentage deviation from steady state.

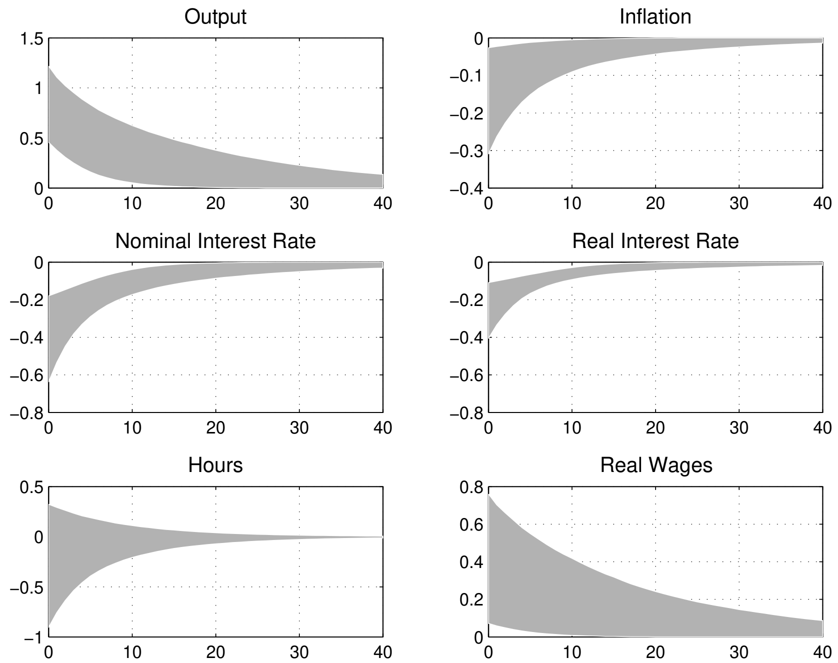

Figure 6: Theoretical impulse responses to technology surprise shocks: Simulation exercise. Note: Based on 10,000 draws. Gray shaded area is the pointwise difference between the 84^{th} and 16^{th} percentiles of the posterior distribution. x-axis: quarters; y-axis: percentage deviation from steady state.

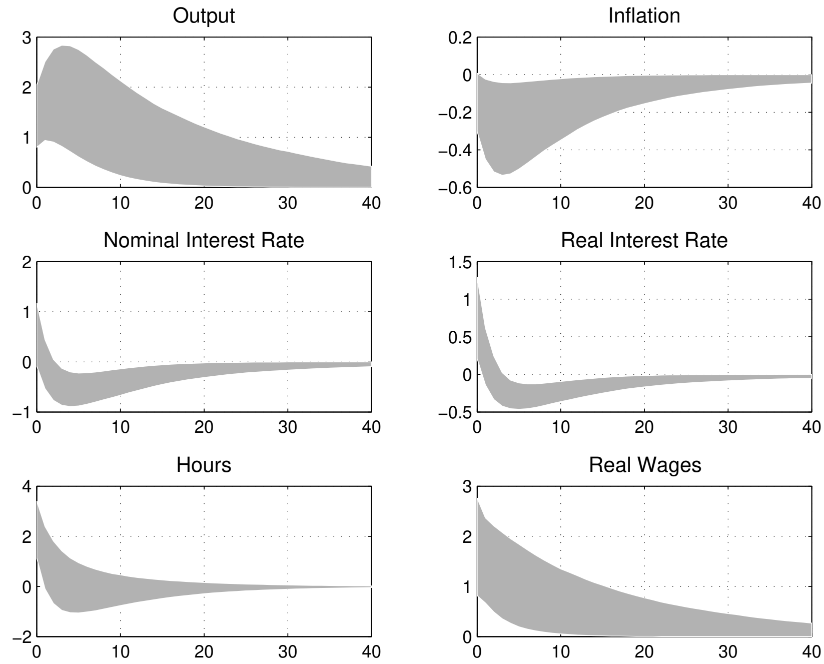

Figure 7: Theoretical impulse responses to technology news shocks: Simulation exercise. Note: Based on 10,000 draws. Gray shaded area is the pointwise difference between the 84^{th} and 16^{th} percentiles of the posterior distribution. x-axis: quarters; y-axis: percentage deviation from steady state.

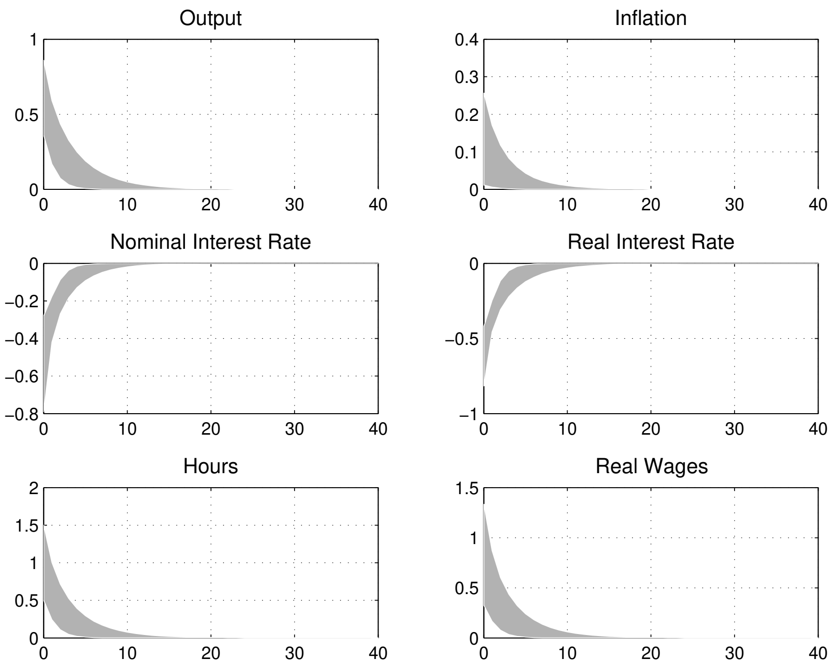

Figure 8: Theoretical impulse responses to monetary policy shocks: Simulation exercise. Note: Based on 10,000 draws. Gray shaded area is the pointwise difference between the 84^{th} and 16^{th} percentiles of the posterior distribution. x-axis: quarters; y-axis: percentage deviation from steady state.

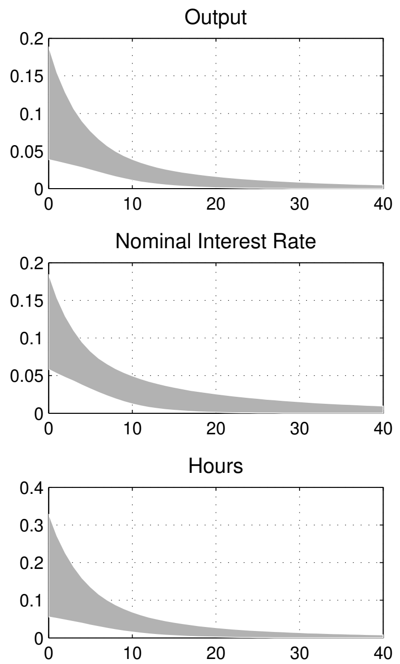

Figure 9: Theoretical impulse responses to preference shocks: Simulation exercise. Note: Based on 10,000 draws. Gray shaded area is the pointwise difference between the 84^{th} and 16^{th} percentiles of the posterior distribution. x-axis: quarters; y-axis: percentage deviation from steady state.

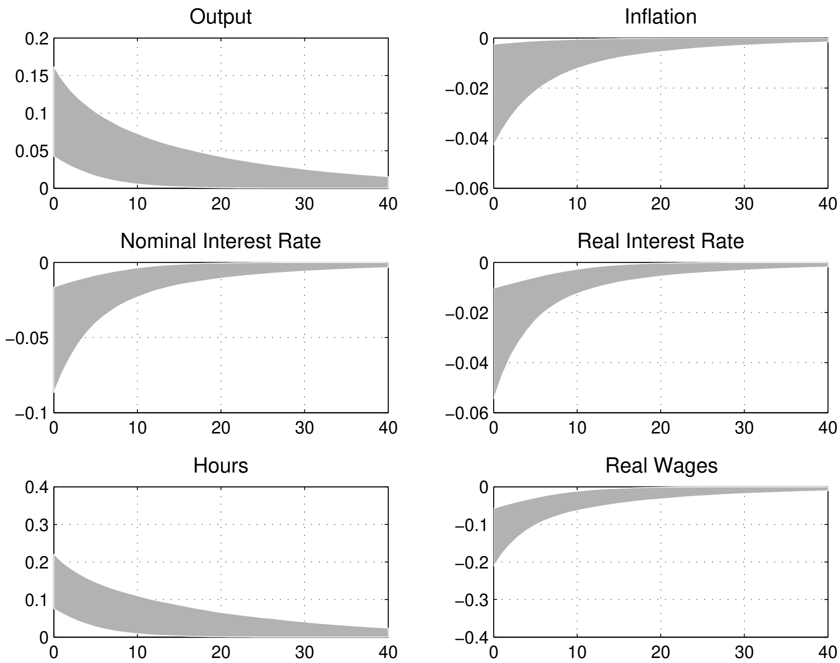

Figure 10: Theoretical impulse responses to labor supply shocks: Simulation exercise. Note: Based on 10,000 draws. Gray shaded area is the pointwise difference between the 84^{th} and 16^{th} percentiles of the posterior distribution. x-axis: quarters; y-axis: percentage deviation from steady state.

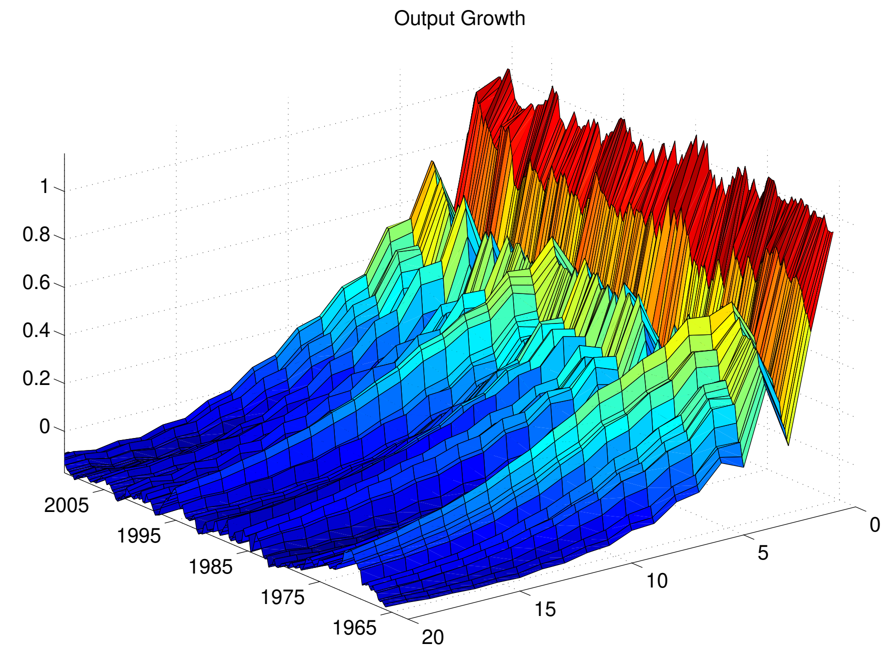

Figure 11: Time varying impulse responses to technology news shocks: Output growth. Note: Shows the posterior mean. x-axis (reversed): quarters; y-axis: time; z-axis: percent.

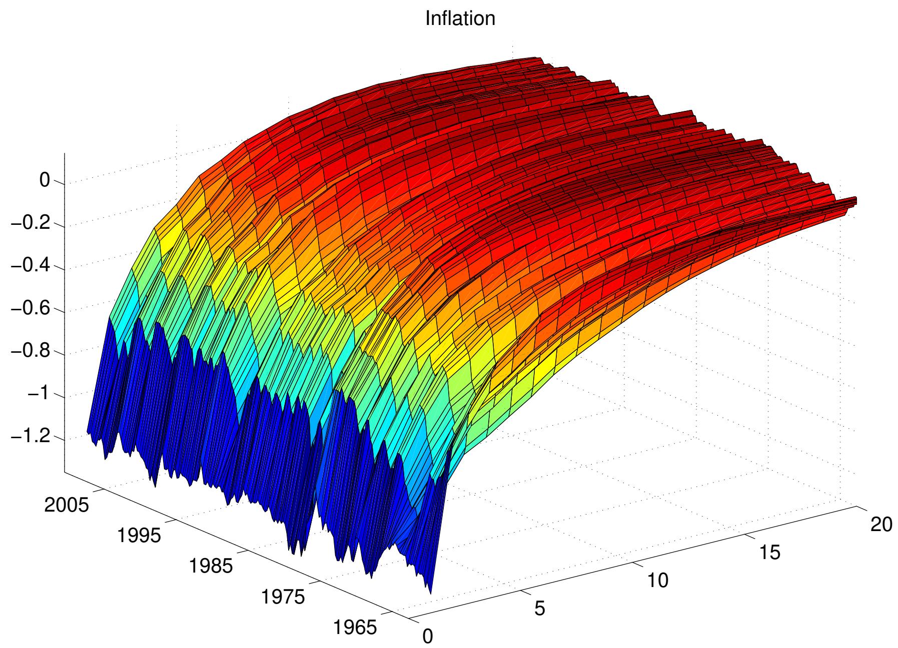

Figure 12: Time varying impulse responses to technology news shocks: Inflation. Note: Shows the posterior mean. x-axis: quarters; y-axis: time; z-axis: percentage points.

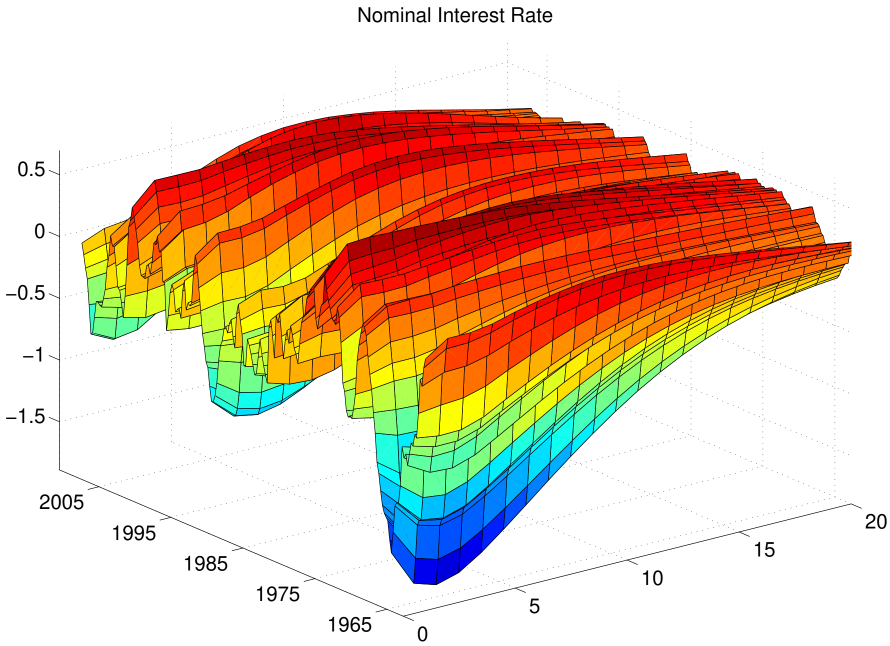

Figure 13: Time varying impulse responses to technology news shocks: Nominal interest rate. Note: Shows the posterior mean. x-axis: quarters; y-axis: time; z-axis: percentage points.

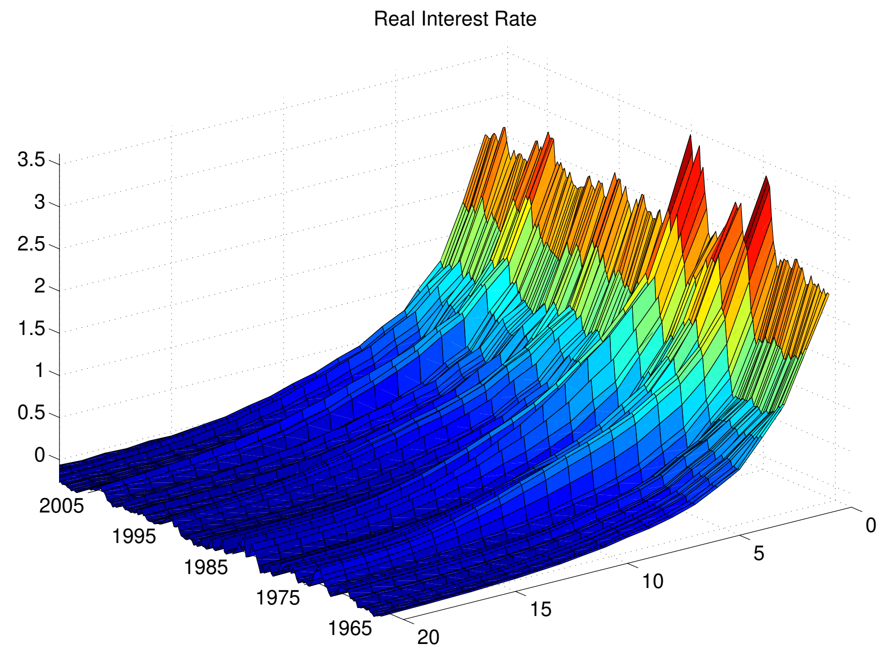

Figure 14: Time varying impulse responses to technology news shocks: Real interest rate. Note: Shows the posterior mean. x-axis (reversed): quarters; y-axis: time; z-axis: percentage points.

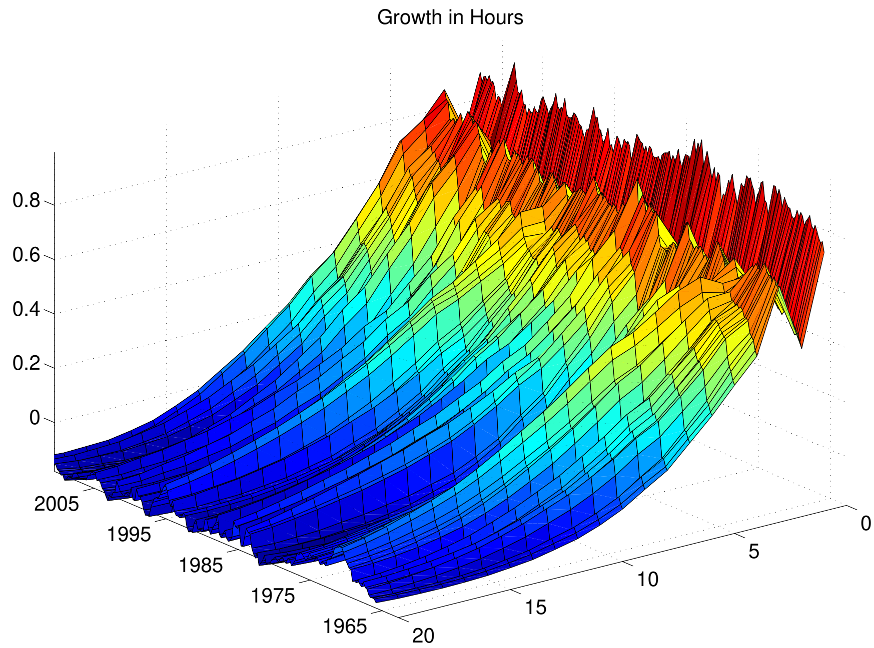

Figure 15: Time varying impulse responses to technology news shocks: Growth in hours worked. Note: Shows the posterior mean. x-axis (reversed): quarters; y-axis: time; z-axis: percent.

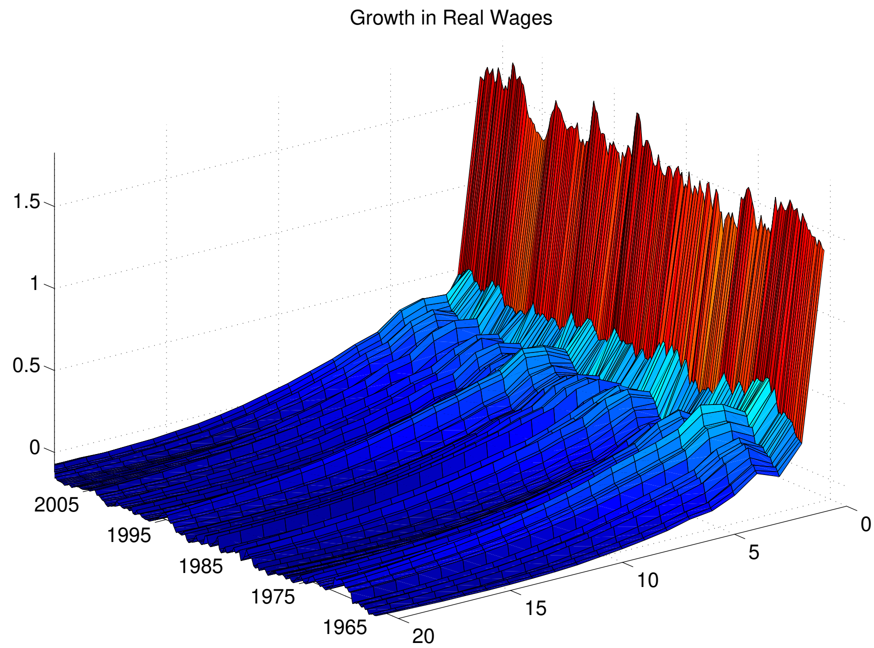

Figure 16: Time varying impulse responses to technology news shocks: Growth in real wages. Note: Shows the posterior mean. x-axis (reversed): quarters; y-axis: time; z-axis: percent.

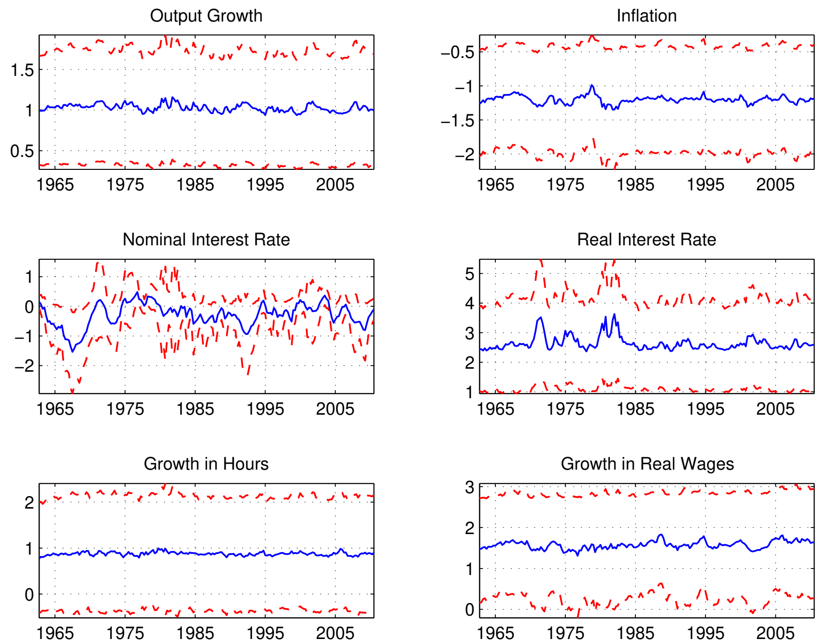

Figure 17: Time varying impulse responses to technology news shocks on impact. Note: Shows the posterior mean (solid) with 68 percent confidence interval (dashed). x-axis: time; y-axis: percent/percentage points.

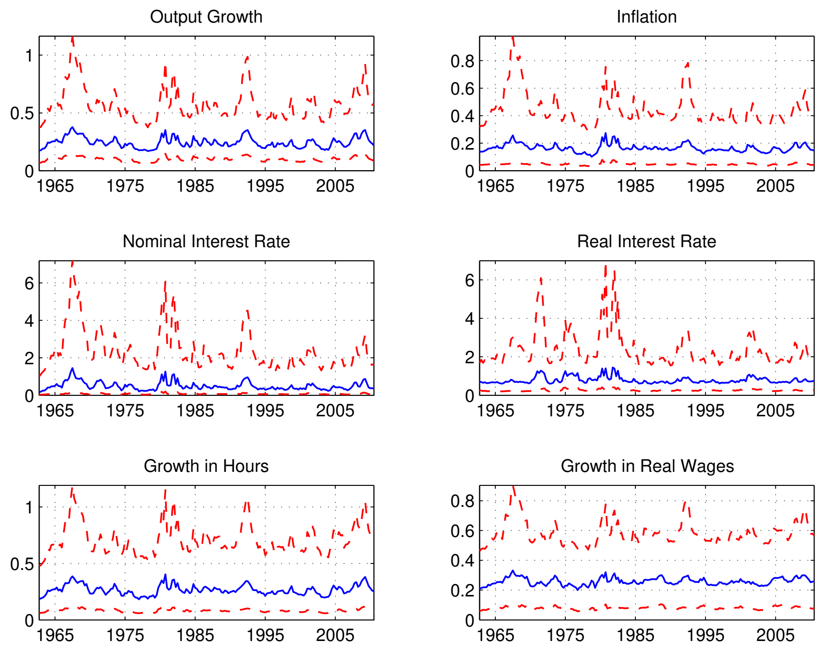

Figure 18: Volatility due to technology news shocks. Note: Shows the posterior median (solid) with 68 percent confidence interval (dashed). x-axis: time; y-axis: posterior variance.

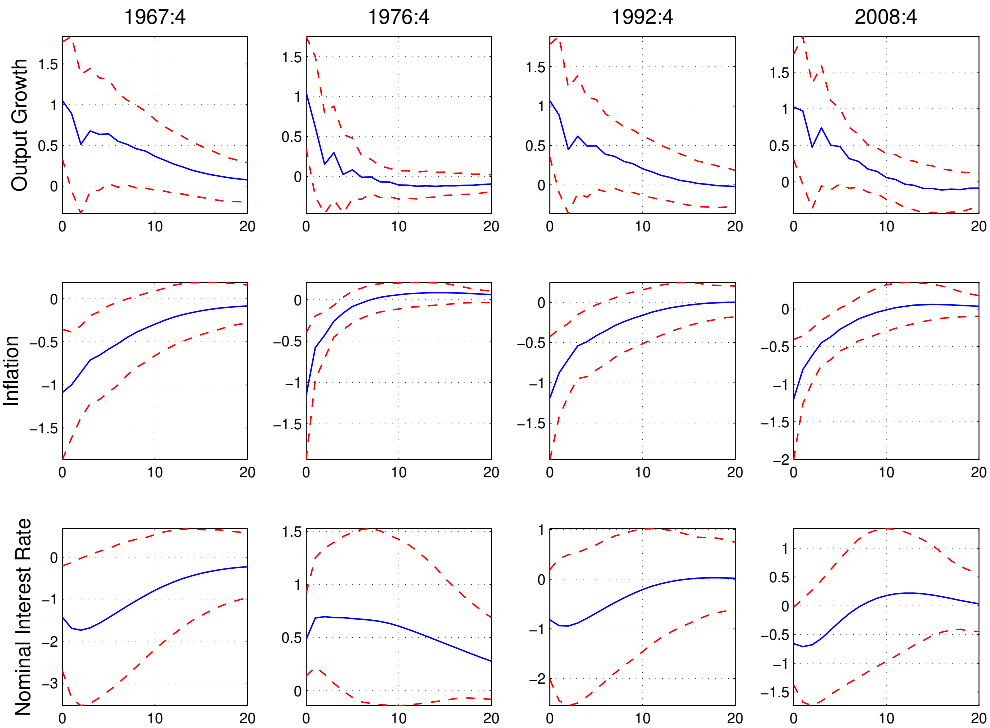

Figure 19: Impulse responses to technology news shocks at selected dates. Note: Shows the posterior mean (solid) with 68 percent confidence interval (dashed). x-axis: quarters; y-axis: percent/percentage points.

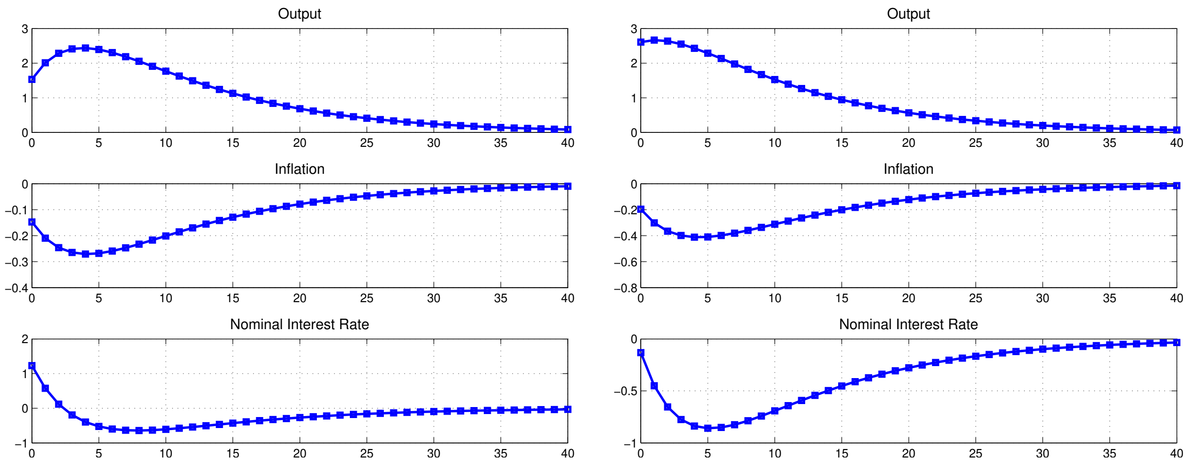

Figure 20: Theoretical impulse responses to technology news shocks for different monetary policy regimes. Note: Interest rate rule with weak response to inflation ($\phi_\pi = 1.01$) and strong response to output gap ($\phi_y = 0.9$) (left panel). Interest rate rule with strong response to inflation ($\phi_\pi = 2$) and weak response to output gap ($\phi_y = 0.1$) (right panel). x-axis: quarters; y-axis: percentage deviation from steady state.