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ABSTRACT

What Does A Technology Shock Do? A VAR Analysis with Model-based Sign Restrictions*

This Paper estimates the effects of technology shocks in VAR models of the United States, Japan and Germany, identified imposing restrictions on the sign of impulse responses. These restrictions are motivated with priors on the parameters of a class of DSGE models with both real and nominal frictions. Estimated technology shocks lead to substantial and persistent increases in labour productivity, real wages, consumption, investment and output. In contrast with most results in the VAR literature, hours worked are much more likely to increase, displaying a hump-shaped pattern. These results are shown to stem primarily from the identification strategy proposed in the Paper, which substitutes theoretical restrictions for the atheoretical assumptions on the time series properties of the data, that are the hallmark of long-run restrictions.

JEL Classification: C30 and E30
Keywords: Bayesian VAR methods, DSGE models, impulse responses and technology shocks

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1 Introduction

An important task of macroeconomics is to develop models that account for specific, quantitative features of the business cycle. In driving the bulk of the aggregate fluctuations observed in the postwar U.S. economy, modern business cycle theory envisions a central role of technology shocks. As shown in the seminal work of Kydland and Prescott [1982], when technology shocks as volatile and persistent as estimated total factor productivity (TFP) are fed through a standard real business cycle (RBC) model, the simulated economy appears to be able to replicate the patterns of *unconditional* volatilities and cross-correlations of key macroeconomic time series.

The predictions of the RBC theory, however, have also been compared to actual *conditional* moments, i.e. conditional on technology shocks being the source of fluctuations, with less flattering results. Galí [1999], instead of interpreting TFP innovations as technology shocks, with structural VAR methods identifies technology shocks as the only source of a unit root in labor productivity. In stark contradiction to standard RBC theory, after a positive technology shock he estimates a fall in hours worked so persistent that it entails a negative conditional correlation between output and hours worked. Because the latter are in fact strongly procyclical unconditionally, Galí [1999] concludes that some other shock(s) must be driving aggregate fluctuations.[1]

This paper reconsiders the important, VAR-based evidence on the dynamic effects of technology shocks and thus their role in accounting for business cycle fluctuations.[2] Technology shocks are identified by means of restrictions on the sign of impulse responses, similarly to the approach proposed by Canova and De Nicoló [2002], Faust [1998] and Uhlig [2001] for monetary policy shocks. Differently from the above papers, however, the degree of agnosticism inherent in this kind of restrictions explicitly reflects a priori uncertainty on the parameters of a class of widely used dynamic general equilibrium (DSGE) models (e.g., see Christiano, Eichenbaum and Evans [2003]). These models, though implying that across all parameterizations the responses of several variables to a positive shock to technology are positive for a number of quarters, are rather uninformative concerning the effect on hours worked. The latter can either increase or fall depending on the values of key preference and technology parameters, independently of the presence of nominal rigidities.[3]

[1] Other recent papers, using different methodologies, have called into question the notion that technology shocks have anything to do with business cycles (see, e.g., Shea [1998], Basu, Fernald and Kimball [1998]).

[2] The relevance of this issue cannot be overemphasized. An invited session of the 2003 meeting of the European Economic Association was entirely devoted to debating it (see the related issue of the Journal of the European Economic Association). See also the survey in Galí and Rabanal [2004] and the comments by McGrattan [2004] and Ramey [2004].

[3] Francis and Ramey [2003] argue that real business cycle models, suitably modified to allow for habit formation

The identification strategy implemented in this paper aims at substituting weak theoretical restrictions for the atheoretical, auxiliary assumptions on the time series properties of the data, that are key in the identification strategy based on long-run restrictions. As argued by Cooley and Dwyer [1998], the latter approach crucially relies on the distinction between the almost observationally equivalent trend- and difference-stationarity of variables that, although inconsequential for many purposes, could make the implied dynamics of the VAR model quite sensitive to misspecification of these auxiliary assumptions. In this vein, Christiano, Eichenbaum and Vigfusson [2003] document that the estimated effects of technology shocks identified with long-run restrictions are quite sensitive to whether some variables enter the VAR in levels or first differences.[4]

The economic restrictions on the sign of the responses of variables used in this paper, by contrast, are appealing for the following two reasons. First, while models with different implications are conceivable, these restrictions are likely to enjoy a fairly broad support as they are derived for a wide range of parameterizations of a class of models similar to those estimated by Christiano, Eichenbaum and Evans [2003] and Smets and Wouters [2003], encompassing most frictions proposed in the macroeconomic literature, like habits formation in consumption, investment adjustment costs, variable capacity utilization and nominal rigidities.

Second, sign restrictions are weak in the sense that they lead to a plurality of candidate structural impulse responses. Rather than as a shortcoming, this is a potentially important advantage of this approach, for it eschews "incredible" exact restrictions, such as exclusion restrictions, that are likely not to be robust to small perturbations to model specification. For instance, our restrictions are valid independently of the fact that technology shocks be exactly nonstationary and the only source of a stochastic trend in labor productivity.[5]

When we apply this methodology to VAR models of the U.S., Japan and Germany we find that a positive shock to technology leads to a significant and persistent rise in labor productivity, real wages, output, consumption and investment, and, in line with the predictions of standard RBC models, it

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and capital adjustment costs, may be consistent with Galí [1999] findings. The latter contribution originally suggested nominal rigidities as the most natural explanation for the negative response of hours worked.

[4]Other recent papers have disputed the very result that hours fall after a technology improvement in VARs, by either challenging its robustness or radically questioning the "credibility" of long-run restrictions for identifying technology shocks. For instance, Uhlig [2003] shows that medium run restrictions may be more robust to some model misspecification than long-run restrictions. Chari, Kehoe and McGrattan [2004], instead, argue that even in slightly misspecified structural VARs long-run restrictions are worringly prone to yielding mistaken inferences.

[5]For instance, Fisher [2002] and Uhlig [2003] convincingly argue that a unit root in labor productivity may results from permanent shocks different from the standard RBC shock to TFP.

is much more likely to drive hours worked up, not down. With a 4/5 probability, a typical shock will increase U.S. hours worked after one year. In addition, these results are consistent with the view that technology shocks play an important role in accounting for output fluctuations, although the uncertainty surrounding the contributions of these shocks to the variance of the forecast errors is large. Moreover technology shocks leave unexplained most of the variation in hours worked.[6]

In light of the controversy about the estimation of the effects of technology shocks with long-run restrictions, we investigate whether our findings are sensitive to modelling the variables in the VAR — notably per capita hours worked — in levels or first differences.[7] Moreover, we verify their robustness to subsample stability, and to the assumption of a diffuse prior on the reduced form coefficients of the VAR, entertained in our Bayesian inferential approach. In all three cases we find that the results are not affected by these assumptions. But what can then account for the differences between our findings and those obtained with long-run restrictions?

We address this question in three steps. First, we make sure that our approach does not have any inherent bias toward finding an increase in hours worked. We do this by showing that, when applied to simulated data from a model parameterized so that hours worked fall after a technology shock, it can recover the correct negative sign. Second, we argue that our approach is very unlikely to mix up technology shocks with other shocks that may entail a (more) positive response of labor inputs, like monetary policy shocks, price markup shocks, investment-efficiency and capital-income tax shocks. Finally, after having ruled out these spurious explanations, we show that our findings result, more obviously, from differences in the identification strategies. Even when we focus on those structural impulse vectors that explain a large fraction of labor productivity in the long run, we always find that hours worked, regardless of how uncertain their response on impact might be, sharply rise with a hump-shaped pattern. Moreover, this kind of impulse responses yielding dynamic effects similar to those estimated with long-run restrictions are relatively unlikely. Most structural impulse vectors uncover technology shocks whose long run effects are somehow smaller and less persistent, and bring about an increase in hours worked within the first few quarters. Overall, our results suggest that long run restrictions, among which atheoretical assumptions on the VAR specification play a crucial role, are not consistent with our identifying assumptions, explicitly rooted in economic theory.

The remainder of the paper is organized as follows. Section 2 briefly outlines the benchmark

[6]See Kydland [1995] about the well-known fact that hours worked are too volatile in the data, relative to the predictions of standard RBC models.

[7]See for instance Christiano, Eichenbaum and Vigfusson [2003] and Galí and Rabanal [2004].

model, and reports the theoretical impulse responses of a selected vector of variables that are used to identify technology shocks. Section 3 presents our identification approach, while Section 4 illustrates the results of the VAR analysis in terms of impulse responses and variance decomposition. In Section 5 the determinants of our results are investigated. Finally, Section 6 offers some concluding observations.

2 Labor inputs dynamics in a DSGE model with real and nominal frictions

In this section we describe the model that is used as a laboratory to analyze the response of a set of variables to technology shocks. The model is basically the one estimated by Christiano, Eichenbaum and Evans [2003] for the U.S. and Smets and Wouters [2003] for the euro area. It features both real rigidities, in the form of adjustment costs for investment and variable capacity utilization, and nominal rigidities, namely sticky prices and wages. To save on space, we present only the linearized equations of the model, following the convention that a hat denotes deviations of variables either from their baseline long-run growth path (e.g. real consumption) or from their steady state (e.g. inflation). We will then consider impulse responses to technology shocks. Since we are interested in implications in terms of the signs of the responses of variables that are robust across a broad range of parameterizations of the model, with and without nominal rigidities, we find it useful to assume that all structural parameters are uniformly and independently distributed over sufficiently wide ranges. Given the fundamental uncertainty on the best way to model the long-run behavior of hours in the U.S., a main advantage of our approach is that it leaves this behavior unspecified in the model, as preferences are not restricted so that hours be stationary along the balanced growth path. This is consistent with our level specification of the VAR, that is agnostic on the best way to model the long-run properties of the data.

2.1 The real side of the economy

The explicit consideration of a balanced growth path in which per capita real variables grow at the rate $1 + g$ implies that the subjective discount factor β in the linearized economy has to satisfy the following restriction, $\beta = b\,(1+g)^{1-\sigma_c}$, as shown by King and Rebelo [1999], where $b \in [0.985, 0.995]$ is the discount factor in the level economy, implying an interest rate between 2% and 6.5% per annum — this latter value is the one assumed in King and Rebelo [1999]. We set $g = 0.004$, equal to the trend in U.S. labor productivity per hour worked over the 1955:1-2001:4 period. This implies a 1.6% annual growth rate in per capita output, investment and consumption.[8] Notably, when models of this type are estimated the discount factor is usually calibrated to a particular value, even though it is an important determinant of the dynamics of wage and inflation when nominal rigidities are considered, as shown below.

Fluctuations in the model economy around the balanced growth path are driven by the standard RBC technology shock affecting total factor productivity, ϵ^z, and by an investment-specific technology shock, ϵ^i (see Greenwood, Hercowitz, and Huffman [1998], and Greenwood, Hercowitz, and Krusell [2000]).[9] As is customary in the macro literature, both shocks are assumed to have an autoregressive representation of order one with a coefficient $\rho_j \in [0.75, 0.999]$, $j = z, i$. This parameterization does not formally encompass the case of an economy with unit root shocks to productivity; however the latter behavior is basically indistinguishable, in samples of the length of the U.S. postwar period, from that induced by values close to the upper bound of the assumed range of the autoregressive coefficients. Notice that at this stage we do not need to take a stand on the standard deviation of the shocks innovations, as the sign of the impulse responses will be invariant to it.

We consider both types of technology shocks for the following reason. In contrast to the standard RBC technology shock, ϵ^i_t does not have any immediate impact on the production function. Instead, it affects the rate of transformation between current consumption and productive capital in the future. Thus, any effects on current output must be the result of the ability of that shock in eliciting a change in the quantity of input services hired by firms. As argued by Galí and Rabanal [2004], this implies that in a model with nominal rigidities ϵ^z and ϵ^i can have different effects on hours worked but similar effects on the other variables of interest, like output and labor productivity. Therefore, it is important to investigate whether these two different kinds of technology shocks can be distinguished on the basis of their dynamic effects on a larger set of variables.[10]

[8] Our results below in terms of sign restrictions are not affected when we consider the higher growth rate implicit in per capita consumption and investment, equal to 2.4% per annum.

[9] In a previous version of the paper we also illustrated the effects of shocks to capital income taxation, which have been suggested by some authors (e.g., Uhlig [2003]) as posing a problem in identifying technology shock with long-run restrictions. Since these shocks bring about very similar effects to those arising from investement specific shocks, we do not report results on them here. However, we will return to this issue in Section 5, when dicussing the robustness of our results.

[10] The argument in Galí and Rabanal [2004] is made informally in the context of a sticky price version of a model like that of Greenwood, Hercowitz and Krusell [2000], assuming for simplicity that the relationship $y_t = m_t - p_t$ holds in equilibrium, and that both m_t and p_t are pre-determined relative to the shock. In that case firms will want to produce

Given our assumption of separability between consumption and leisure, the Euler equation for consumption $\hat{c}_t$ is given by:

$$\hat{c}_t = \frac{h}{1+h}\hat{c}_{t-1} + \frac{1}{1+h}E_t\hat{c}_{t+1} - \frac{1-h}{(1+h)\,\sigma_c}\left(\hat{R}_t - E_t\hat{\pi}_{t+1}\right) \tag{1}$$

where the parameter $h \in [0.0, 0.8]$ measures the degree of habit formation, and the parameter $\sigma_c \in [1.0, 10]$ measures the inverse of the intertemporal elasticity of substitution for consumption (i.e., the risk aversion coefficient). The assumed ranges encompass most valued used and estimated in the literature. For instance the largest point estimate of h reported by Christiano, Eichenbaum and Evans [2003] is 0.71 (with a standard error of 0.03); these authors also set $\sigma_c = 1$. The variables $\hat{R}_t$ and $\hat{\pi}_{t+1}$ denote the nominal short-term interest rate and the inflation rate, respectively, that in the RBC economy are separately determined by the monetary policy rule, with no feedback to real variables.

Because of adjustment costs, households choose the level of investment and capital according to the following linearized first order condition for investment:

$$\hat{\imath}_t = \frac{\beta}{1+\beta}E_t\hat{\imath}_{t+1} + \frac{1}{1+\beta}\hat{\imath}_{t-1} + \frac{\chi^{-1}}{1+\beta}\hat{q}_t + \frac{\beta}{1+\beta}E_t\epsilon^i_{t+1} - \frac{1}{1+\beta}\epsilon^i_t \tag{2}$$

where $\hat{q}_t$ is the price of installed capital goods in terms of consumption goods (Tobin's q), $\hat{\imath}_t$ is the level of investment, $\chi \in [0.0, 5.0]$ is the inverse of the elasticity of investment to the price of capital goods. The parameter χ is inversely related to the steady state value of the second derivative of the investment adjustment cost function. The largest point estimate in Christiano, Eichenbaum and Evans [2003] for this parameter is 3.24 (with a standard error of 0.47).[11]

The optimal choice for the stock of capital is given by:

$$\hat{q}_t = -\left(\hat{R}_t - E_t\hat{\pi}_{t+1}\right) + \beta\,(1-\delta)\,E_t\hat{q}_{t+1} + \beta\overline{r}E_t\hat{r}_{t+1} \tag{3}$$

where $\hat{r}_t$ ($\overline{r}$) is (the steady state value of) the rental price of capital (determined solely by β and δ), and δ is the depreciation rate, usually assumed to be equal to 0.025 in the RBC literature (see Cooley and Prescott [1995]). Because of variable capacity utilization, the following approximate

the same quantity of the good but, in contrast with the case of neutral technology shocks, in order to do so they will need to employ the same level of inputs since the efficiency of the latter has not been affected (only newly purchased capital goods will enhance that productivity in the future). Notice, however, that to increase investment and reap the benefit of the shock, consumption will have to decline, given that output is fixed.

[11] See Christiano, Eichenbaum and Evans [2003] on the specific form of this adjustment cost function and a discussion of its properties.

relation exists between the rental rate of capital and capacity, $\widehat{u}_t$:

$$\psi \hat{r}_t = \widehat{u}_t, \tag{4}$$

where $\psi \in [0.0, 50]$ is the elasticity of capital utilization with respect to the rental rate of capital. Thus, a zero value of ψ corresponds to the standard case in which capacity does not adjust. This parameter is not estimated by Christiano, Eichenbaum and Evans [2003], but set to 100 a priori.

The aggregate resource constraint and the capital accumulation equations close the real side of the economy:

$$\begin{aligned} \frac{\alpha\delta}{\overline{r}}\widehat{i}_t + \left(1 - \frac{\alpha\delta}{\overline{r}}\right)\widehat{c}_t &= \alpha\widehat{k}_t + (1-\alpha)\,\hat{l}_t + \alpha\psi\hat{r}_t + \hat{\epsilon}^z_t, && (5)\\ \widehat{k}_{t+1} &= \delta\widehat{i}_t + (1-\delta)\,\widehat{k}_t, && (6) \end{aligned}$$

where the variable $\hat{\epsilon}^z_t$ represents the standard technology shock shifting the production possibility frontier, $\hat{l}_t$ is hours worked, $\hat{k}_t$ is the capital stock, while α is the capital share in the (Cobb-Douglas) production function, usually assumed to be around 1/3 in the RBC literature (see Cooley and Prescott [1995]). Notice that because of variable capacity utilization aggregate output is a function of the return on capital $\hat{r}_t$.

2.2 Nominal rigidities and monetary policy

Nominal rigidities are introduced in the form of both wage and price stickiness. Households choose the level of nominal wage for the type of labor they supply in order to maximize their intertemporal utility function. As shown by Smets and Wouters [2003], the log-linearization of the first order condition for this problem delivers the following real wage equation:

$$\begin{aligned} \hat{w}_t \;=\;& \frac{\beta}{1+\beta}E_t\hat{w}_{t+1} + \frac{1}{1+\beta}\hat{w}_{t-1} + \frac{\beta}{1+\beta}E_t\hat{\pi}_{t+1} - \frac{1+\beta\gamma_w}{1+\beta}\hat{\pi}_t + \frac{\gamma_w}{1+\beta}\hat{\pi}_{t-1}\\ & -\frac{1}{1+\beta}\frac{(1-\beta\xi_w)(1-\xi_w)}{\left(1+\frac{(1+\lambda_w)\sigma_l}{\lambda_w}\right)\xi_w}\left[\hat{w}_t - \sigma_l\hat{l}_t - \frac{\sigma_c}{1-h}(\hat{c}_t - h\hat{c}_{t-1})\right] \end{aligned} \tag{7}$$

where $\hat{w}_t$ is the real wage. The parameter $\xi_w \in [0.0, 0.8]$ measures the probability that the wage is not reoptimized in every period. The higher this parameter, the more sticky wages will be. The lagged term of the real wage $\hat{w}_{t-1}$ is introduced assuming that wages that are not chosen optimally are indexed to last period inflation rate. The parameter $\gamma_w \in [0.0, 1.0]$ measures the degree of indexation of wages to last period inflation. The larger this parameter, the more nominal wages are persistent. Clearly, the standard Euler equation for the labor choice under flexible wages, appearing in the above equation in brackets, is obtained by setting $\xi_w = \gamma_w = 0$. Christiano, Eichenbaum and Evans [2003], while setting $\gamma_w = 1$, report estimates of ξ_w within the above range, with a maximum value equal to 0.8. The parameter $\sigma_l \in [0.0, 10]$ measures the inverse of the elasticity of the labor supply. Finally, $\lambda_w \in [0.0, 1.0]$ measures the wage-setter markup, ranging from 0 to 100 percent.

The inflation equation:

$$\hat{\pi}_t = \frac{\beta}{1+\beta\gamma_p} E_t \hat{\pi}_{t+1} + \frac{\gamma_p}{1+\beta\gamma_p} \hat{\pi}_{t-1} + \frac{1}{1+\beta\gamma_p} \frac{(1-\beta\xi_p)(1-\xi_p)}{\xi_p} \left[\alpha \hat{r}_t^k + (1-\alpha)\hat{w}_t - \hat{\epsilon}_t^z\right] \tag{8}$$

is derived by linearizing the first order condition of the optimization problem of monopolistic competitive firms who choose the price to be set in order to maximize the expected discounted stream of future profits (see Smets and Wouters [2003]).

Allowing firms that do not reoptimize their price to adjust it to last period inflation rate delivers an equation in which current inflation depends on last period inflation. The parameter $\xi_p \in [0.0, 0.8]$ measures the probability the price of a good is not reoptimized in the current period. The higher this parameter, the more prices will be sticky. The parameter $\gamma_p \in [0.0, 1.0]$ measures the degree of indexation of prices. The larger this parameter, the more inflation is persistent. Again, setting $\xi_p = \gamma_p = 0$ recovers the standard expression for marginal costs with flexible prices and Cobb-Douglas production function, in brackets in the above equation. Christiano, Eichenbaum and Evans [2003], while setting $\gamma_w = 1$, report a maximum estimate of ξ_p equal to 0.92, but argue that this value is way to high given the evidence on individual price changes in Bils and Klenow [2002], implying that firms change prices roughly every 5 months on average. Therefore we set the upper limit to 0.8 — implying that the average duration of prices is 5 quarters at most.

Finally, the monetary authority sets the short-term interest rate according to the following Taylor rule:

$$\hat{R}_t = (1-\rho_r)\rho_y \hat{y}_t + (1-\rho_r)\rho_\pi \hat{\pi}_t + \rho_r \hat{R}_{t-1}, \tag{9}$$

with parameters $\rho_r \in [0.0, 0.99], \rho_y \in [-0.25, 0.25], \rho_\pi \in [1.1, 2.0]$, encompassing most values estimated in the literature.

2.3 Translating priors on parameters into restrictions on impulse responses

We now present and discuss the impulse responses of the model's variables to productivity shocks, with a view to deriving identifying restrictions on their sign.[12] This identification strategy is very

[12] We report impulse responses only for these shocks because the model has implications that would allow us to disentangle other shocks considered in the literature, like labor supply shocks (akin to labor tax rate shocks) and

much in line with the methodology outlined by Canova [2002] for VARs. In order to formally derive restrictions on impulse responses, we assume that all structural parameters are uniformly and independently distributed over sufficiently wide ranges. Table 1 summarizes the ranges of the uniform distributions for the parameters of the model including real and nominal frictions. As argued above, these ranges cover reasonable values for the parameters, encompassing most estimates in the literature. Clearly, priors for the RBC model augmented with real frictions can be derived as a particular case in which the (degenerate) priors over the relevant parameters (namely, $\xi_p, \gamma_p, \xi_w, \gamma_w, \lambda_w, \rho_r, \rho_y, \rho_\pi$) have all the probability mass concentrated at zero.

In principle, our uniform priors on structural parameters would transpire into a pattern of impulse responses that have richer implications than the sign restrictions we use in recovering structural shocks in the data. However, two considerations lead us to focus on sign restrictions only. First, the latter are more likely to be robust to changes in the specification of the functional form of the priors on the structural parameters of the model economy. In this sense our own uniform prior on parameters can be thought as a convenient device to put discipline on the derivation of sign restrictions on impulse responses. Second, it is computationally more viable to impose sign restrictions in the context of Bayesian VARs, rather than a whole shape of the implied distribution of impulse responses, thus allowing to use standard available methods for estimation and inference.

In order to derive robust implications for the responses to technology shocks we carried out the following Monte Carlo simulation. We drew a large number of vectors of parameters from the distributions reported in Table 1 for the RBC model and the model with nominal rigidities (henceforth NR). For each draw we saved the responses to a one per cent positive neutral technology and investment-efficiency shock, and computed the 2.5 and 97.5 percentiles of their distributions point-by point. This ensures that parameters combinations that bring about extreme responses in the tails are ruled out.[13]

The results are reported in Figures 1A to 1D, displaying impulse responses up to 20 quarters.

preference shocks, from technology shocks. To save on space we do not report these impulse responses, that are available upon request.

[13]For instance this can occur because of parameter values implying singularity of some of the matrices of the model's state space representation. In addition, since several parameterizations of the monetary policy rule in the nominal rigidities economy may transpire into local indeterminacy of the steady state, we discard draws that imply local indeterminacy. Clearly, in the presence of sunspots any exercise in identification of impulse responses to orthogonal shocks would be rather meaningless. See Lubik and Schorfheide [2004] for a estimated DSGE model that allows for indeterminacy.

From Figures 1A and 1B, presenting the dynamic effects of a 1 percent positive shock to ϵ_t^z, it is clear that neutral technology shocks have qualitatively similar effects on real variables irrespective of nominal rigidities. Labor productivity, real wages, output, investment and consumption increase for several quarters. However, these positive responses can be more or less persistent, and revert to steady state more or less slowly, reflecting our rather uninformative priors on both the parameters governing the internal propagation mechanism and the serial correlation of the shocks. Moreover, for both the RBC and NR prior, hours worked can either fall or rise depending on the parameterization, not only on impact but up to 20 quarters after the shock, with a median response that is negative for most quarters. Finally, Figure 1B also shows that, for the parameters range considered, the sign of the response of inflation and the short-term interest rate in the nominal rigidities model is a priori indeterminate as well. However, both variables always move in the same direction on impact, implying a positive correlation in the first quarter at least.

What about investment efficiency shocks? In Figures 1C and 1D we report the 2.5 and 97.5 percentiles of the impulse responses to a 1 percent positive shock to ϵ_t^i. Figure 1C shows that, in a model without nominal rigidities, these shocks have radically different implications for many variables, relative to the neutral technology shock. In particular, in the face of an investment and output increase triggered by a rise in hours worked, they bring about a decline of consumption and labor productivity in the first few quarters. Interestingly, this occurs notwithstanding the fact that the model features variable capacity utilization, so that all these variables could in principle increase when hours increase.

Conversely, Figure 1D shows a less clear-cut picture for the (NR) model with nominal rigidities. An expansionary response of systematic monetary policy may bring about an increase in both investment and consumption on impact, by appropriately inducing a magnified increase in hours worked. However, since the benefit of forgoing current consumption for investment in the presence of such a shock is generally quite high, the median response of consumption remains always negative, and its maximum response (the 97.5 percentile), though marginally positive for the first couple of quarters, subsequently becomes negative — in contrast with the dynamic effects of a neutral technology shock displayed in Figure 1B.

Therefore, under the prior on parameter values in Table 1 there is a unique set of restrictions that allow to disentangle these two shocks in the data, independent of the presence of nominal rigidities, as the technology shock entails a more persistent increase in both consumption and investment. Although such a positive comovement could be intuitively brought about by a very expansionary monetary stance in the face of an investment-specific shock, this kind of systematic policy response is quite unlikely when a standard monetary reaction function like (9) is assumed. Since, however, it is conceivable that modifications in the form of the Taylor rule we consider may better capture the reality of the operation of monetary policy in the face of these kind of shocks, in Section 5 we will thoroughly assess the implications of this issue for our empirical findings.[14]

Given these results, we interpret our prior as requiring that a positive technology shock increases labor productivity for the first 20 quarters, investment and output for the first 10 quarters, real wages for 17 quarters from the 3rd to the 20th, and consumption for the first 5 quarters, as summarized in Table 2. The response of hours, inflation and the short-term interest rate are left unrestricted. This is the set of restrictions on the signs of the impulse responses that are imposed in the VAR analysis below. Since we include inflation and the short-term interest rate in our empirical analysis, it is natural to focus on the implications of the model with nominal rigidities. In addition, these implications are also less restrictive and thus more general than those implied by the model with only real frictions.[15]

3 The empirical framework: Estimating technology shocks by means of sign restrictions

In this section we illustrate our approach to the identification of the technology shocks by means of restrictions on the signs of impulse responses. Its basic idea can be described as follows. The vector of the stacked impulse responses of n variables up to k steps to a structural technology shock, as a function of the estimated reduced form coefficients of the VAR, can be thought of as a random variable with support in R^{nk}. Without any kind of prior knowledge, it would be reasonable to assume a multivariate flat prior over the support of all possible responses, given by an hypersphere in R^{nk} centered in 0. The specification of an economic model with a prior on structural parameters allows us to shift all the probability mass to the event that the responses of $m \leq n$ variables (e.g., labor productivity, investment and so on) be positive for $s \leq k$ quarters. All positive responses, however, are still deemed equally probable.

[14] As a similar result may hold for shocks to a capital income tax, we will address this possibility in Section 5 as well.

[15] In a previous version of the paper we also considered a more restrictive "RBC prior", according to which a positive technology shock increases labor productivity, real wages, investment and output for the first 20 quarters, and consumption for the first 6 quarters. Since results are broadly similar across the two priors, in this version of the paper we focus only on the weaker set of restrictions holding in the more general model with nominal rigidities.

These economic restrictions on the sign of the responses of variables are appealing for the following two reasons. First, while theories with different implications can be constructed, these assumptions are likely to enjoy a fairly broad support as they are derived for a wide range of parameterizations of the above workhorse DSGE model with nominal rigidities, variable capacity utilization, habits formation in consumption and investment adjustment costs. Second, sign restrictions are weak in the sense that they lead to a plurality of candidate structural impulse responses for the same reduced form VAR. Rather than as a shortcoming, we consider this as a potentially important advantage of our approach. For instance, our restrictions are valid independently of the fact that technology shocks be exactly nonstationary and the only source of a stochastic trend in labor productivity. Therefore, the full specification of the stochastic structure and long-run properties of the VAR model that is an essential part of structural VARs with long-run restrictions is not needed in our analysis. Indeed, both our theoretical and empirical impulse responses can be interpreted as deviations from a weakly specified long-run baseline consistent with both trend- and difference-stationarity.

As argued by Uhlig [2001], the Bayesian approach, viewing the reduced-form VAR parameters as random variables, is particularly suited to the implementation of sign restrictions. From a Bayesian point of view, sign restrictions amount to attributing probability zero to reduced form parameters realizations giving rise to impulse responses which contravene the restrictions. To the extent that these restrictions do not lead to over-identification, they impose no constraint on the reduced form of the VAR. We can thus use standard Bayesian methods for estimation and inference.

We now proceed to briefly describe our strategy to estimate the dynamic effects of technology shocks by means of sign restrictions, following Canova and De Nicoló [2002], and especially Uhlig [2001]. Both approaches yield nearly identical results. The reduced form of a VAR has the following representation (omitting a constant c):

$$Y_t = B(L) Y_{t-1} + U_t,$$

where the vector Y includes the variables in level. The covariance matrix of the vector of residuals U_t is denoted with Σ. The reduced form can be estimated consistently using ordinary least squares, which, conditional on Gaussian U_t and initial conditions, is equal to the maximum-likelihood (ML) estimator.[16]

Under standard assumptions, identification in the structural VAR literature aims at providing enough restrictions to uniquely solve for the following decomposition of the $n \times n$ estimated covariance

[16] E.g., see Hamilton [1994].

matrix of the reduced-form VAR residuals, Σ, unique up to an orthonormal transformation:

$$\Sigma = A_0 A_0'.$$

This defines a one-to-one mapping from the vector of orthogonal *structural* shocks ν to the reduced form residuals U, $U = A_0 \nu$.

The j-th column of the matrix A_0, a_j, is called an *impulse vector* in $\mathcal{R}^n$, as it maps the innovation to the j-th *structural* shock ν_j into the contemporaneous, impact responses of all the n variables. Proposition 1 in Uhlig [2001] shows that, given an arbitrary (orthonormal) decomposition A_0 of the matrix Σ, any structural impulse vector a_j can be recovered as $A_0 \alpha$, for an appropriate vector α belonging to the hypersphere $\mathcal{S}^n \subset \mathcal{R}^n$ of unitary radius. Natural candidates are either the eigenvalue-eigenvector decomposition of Σ,

$$\Sigma = \left(PD^{\frac{1}{2}}\right)\left(D^{\frac{1}{2}}P'\right) \tag{10}$$

where D is the diagonal matrix of the eigenvalues, P the matrix of the corresponding eigenvectors of Σ, or its Cholesky decomposition.

With the structural impulse vector a_j in hand, the set of all structural impulse responses of the n variables up to the horizon k can then be computed using the estimated coefficient matrix $B(L)$ of the reduced form VAR:

$$X = [I - B(L)]^{-1} a_j.$$

Thus, if the latter matrix of impulse responses X is consistent with our sign restrictions, the vector a_j effectively identifies a technology shock. Since all possible structural vectors a_j consistent with the restrictions on the signs of the impulse responses are equally probable, it is easy to characterize their set by simulation. For a given estimate of the reduced form of the VAR, we draw candidate α vectors from a uniform distribution over $\mathcal{S}^n$, compute the associated impulse vector a_j and impulse response matrix X, discarding those that do not satisfy the assumed sign restrictions.

Obviously, presenting measures of the statistical reliability of estimated impulse responses is also very important. Therefore, we compute error bands for impulse responses by applying standard Bayesian methods. As shown by Uhlig [2001], under a standard reference prior of the Normal-Wishart family on the VAR reduced form parameters $B(L)$ and Σ, and assuming a Gaussian likelihood for the data sample at hand, the posterior density of the reduced-form VAR parameters with the type of restrictions we implement will be just proportional to a standard Normal-Wishart. Therefore it is possible to draw from the posterior distribution of impulse responses consistent with our sign restrictions by jointly drawing from the Normal-Wishart posterior for Σ, $B(L)$ and the uniform over $\mathcal{S}^n$, discarding the realizations that violate the restrictions.[17]

It should be kept in mind that, as pointed out by Uhlig [2001], the sign restriction approach amounts to simultaneously estimating the coefficients of the reduced-form VAR and the impulse vector. Draws of the VAR parameters from their unrestricted posterior which do not permit any impulse vector to satisfy the imposed sign restrictions are discarded as they receive zero prior weight. Therefore, we check below that our results are not driven by the prior on the VAR reduced form but mainly depend on our identifying assumptions.

4 Evidence with the sign-restriction approach

In this section, we begin by specifying the variables that enter in the VAR and the number of lags. We then proceed in illustrating the results on impulse responses and variance decompositions to technology shocks obtained for the U.S. economy, as well as conducting some sensitivity analysis. We conclude with some international evidence on Japan and Germany.

The variables that we include in the VAR are the logarithm of hourly labor productivity, real wages, per capita hours worked, per capita real investment, per capita real consumption, the quarterly gross inflation rate (based on the GDP deflator) and the quarterly gross short-term interest rate.[18] The countries and sample periods are as follows: 1955:1 - 2003:4 for the U.S., 1970:2 - 2002:2 for Japan and 1976:1 1994:4 for the Federal Republic of Germany. All the data are seasonally adjusted. A detailed description of the data and its sources can be found in the Data Appendix. Figures A1-A3 report the variables used in the estimation of the VAR model for the three countries. Based on likelihood methods, we choose 3 lags for the U.S. and 4 lags for Japan and Germany.

4.1 The dynamic effects of technology shocks in the U.S. economy

The estimated impulse responses to a positive technology shock obtained under the restrictions in Table 2 for the United States, and the associated variance decomposition, are presented in Figures 2 and 3. In each case the Figures show the median (the thick, solid line) and the 5th, 16th, 84th and

[17]To draw from this posterior we use the program *montevar* described in the RATS manual (see Rats User Guide, Estima [2000]).

[18]The first five variables are the same as those used by Francis and Ramey [2003] in their U.S. study. Conversely, in its largest, five variable system Galí [1999] includes, beside the ratio of GDP to total hours worked and total hours worked, our last two nominal variables and a monetary aggregate.

95th percentiles (the dashed lines) of the pointwise distribution of the variables responses, obtained from 500 draws from the unitary hypersphere $\mathcal{S}^7$ for each of 1000 draws from the posterior distribution of the reduced form of the VAR. Output per capita is constructed by adding up the responses of labor productivity and hours worked.

The results presented in Figures 2 and 3 are based on around 35000 different impulse vectors a_j identified out of the total of 500000 draws.[19] Figure 2 shows that a positive technology shock determines a sizable increase in labor productivity, the real wage, consumption, investment and output that is also quite persistent: the 16th percentile of the responses of these variables is generally above zero even after 4 full years. The increase in investment is between 2 and 4 times larger than that of output. The response of consumption, generally less strong than that of output, is much more persistent than the assumed 5 quarters, displaying a pattern broadly similar to that of output. While the median response of labor productivity remains pretty much around the level on impact, that of the other variables displays more of a hump shape, reaching a maximum a few quarters after the impact and then declining, more fast in the case of investment. The maximum median response of consumption and output occurs after around 2 years.

Concerning the variables whose responses are left unconstrained by our identifying assumptions, a clear-cut result is obtained for hours worked. The median response of this variable is also positive and hump shaped, reaching a peak between 5 and 8 quarters after impact, and approaching zero by the 5-year horizon. Around its peak, this response is positive with over 0.8 probability in each single period for 6 quarters. This finding stands out against the fall estimated in the VAR literature studying technology shocks — with the notable exception of Christiano, Eichenbaum and Vigfusson [2003].

Conversely, the effects of technology shocks on the short-term nominal interest rate and inflation in the U.S. appear largely inconclusive. While the response of inflation is more likely to be slightly negative in the first few quarters, with more than a 4/5 probability one quarter after impact, that of the interest rate is basically zero, with equal probability of being either positive or negative. This finding seems to be consistent with our view that both systematic and unsystematic monetary policy are not playing a big role in shaping our results. However, we will explore further this issue in the next subsection and in Section 5.

What are the implications of our estimates in terms of the contribution of the technology shocks

[19] The shapes of the distributions of the impulse responses are extremly robust to increasing the number of draws from both the posterior distribution of the reduced form VAR and the vector α from the unitary hypersphere.

to aggregate fluctuations? We address this issue by computing the percent of the variance of the k-step ahead forecast error that is accounted for by technology shocks. We find that (i) technology shocks cannot be ruled out as an important driving force of business cycles, and (ii) yet, to account for the bulk of cyclical fluctuations in hours (and inflation, interest rates), would require considering other sources of economic disturbances. In this latter respect, our results do not seem dissimilar from those obtained with long-run restrictions.

Figure 3 presents the variance decomposition results at horizons up to 40 quarters, also reporting the median and the pointwise 68 and 90 percent error bands. We see that technology shocks can explain up to over 50 percent of the variability in labor productivity, output, consumption, investment and real wages up to 5 years, although it must be noted that there is a large degree of uncertainty around these estimates. For longer horizons this fraction remains around 50 percent for most variables, with the notable exception of investment. The median fraction, however, is always lower and generally included between 20 and 30 percent. These shocks are very unlikely to come close to explaining 100 percent of the variability of labor productivity at any horizon, thus casting some doubts on identification strategies that exclusively rely on this kind of assumptions.[20]

The explained fraction of variability in hours is generally below 40 percent with 95 percent probability, with a median of around 5-10 percent only. Strikingly, this finding is pretty much in line with the results reported in Galí [1999] and Francis and Ramey [2003]. In this respect, it appears likely that the bulk of movements in hours should reflect shocks different from those affecting technology. However, this fact, i.e. that other shocks than technology shocks would be needed to account for important features of labor markets at business cycle frequency, has been well known to represent a major challenge to RBC theory, since the early contributions of Kydland [1984] and Christiano and Eichenbaum [1992].

Finally, turning to nominal variables, Figure 3 shows that the contribution of technology shocks to the forecast error variance of inflation and especially the short-term interest rate is generally quite limited, with a somehow higher ceiling in the short-run, at most up to 40 percent, falling to below 30 percent in the long run.[21]

[20] As shown by Fisher [2002] investment specific shocks may play an important role in accounting for some of the unexplained variation in labour productivity.

[21] In contrast, Christiano, Eichenbaum and Vigfusson [2003] find that technology shocks identified with long-run restrictions account for over 60 percent of the one step ahead forecast error variance of inflation, and almost 40 percent at even the 20 quarter horizon.

4.2 Sensitivity analysis

In this subsection we investigate to what extent the above results are robust to the following two features of our procedure: (i) the inclusion of the variables in the VAR in levels, and (ii) the adoption of a Bayesian approach with a joint diffuse prior on the VAR reduced form coefficients and the covariance matrix of the residuals.[22] We think the first two checks are important in light of the controversy on the appropriate modelling of the time-series properties of the variables that has surrounded the identification of technology shocks with long-run restrictions. This may raise the legitimate concern that the two assumptions above be a source of bias of our results toward finding a positive response of hours worked.

Throughout our analysis, we have implicitly assumed that there has been no structural change. However, authors like Galí, López-Salido and Vallés [2003], among others, have argued that systematic monetary policy may have changed after 1979, and that resulted in a structural change in VARs parameters and in the effects of technology shocks, especially on hours worked. Therefore we also examine the subsample stability of our results to changes in the U.S. monetary policy regime.[23]

As shown below, it turns out that our findings are quite robust to all these checks. Running our estimation with all real variables in first differences not only does not change our results, but actually leads to an even higher probability of a positive, persistent response of hours to a technology shock. Likewise, our results are not driven by the form of the prior on the VAR reduced form parameters and are robust across the two subsamples considered.

4.2.1 Level vs difference specification

Christiano, Eichenbaum and Vigfusson [2003] show that the findings in Galí [1999] are turned on their head when per capita hours worked are treated as a stationary process rather than as a difference stationary process, as does the latter author. This result has been confirmed by Francis and Ramey [2003] and Galí and Rabanal [2004] with VARs specifications including variables different from those originally used by Christiano, Eichenbaum and Vigfusson [2003]. Since our VAR in levels can be

[22] See Phillips [1991] on how "diffuse" priors can effectively turn out to imply strong restrictions on posterior estimates in the case of nonstationary time series.

[23] Clarida, Galí and Gertler [2000] show that monetary policy became more responsive to changes in expected inflation in the Volcker-Greenspan period. A similar result is obtained by Cogley and Sargent [2003]. On the other hand Sims and Zha [2004] find that changes in the variances of structural shocks are the major source of instability in a VAR that include the main U.S. macroeconomic variables.

viewed as extending that estimated in first differences by Francis and Ramey [2003], for it appends to their five-variable specification inflation and nominal interest rates, it is natural to ask whether our results are also sensitive to our assumption that all variables enter the VAR in levels.

We therefore applied our methodology to a VAR for the U.S. in which labor productivity, hours worked, consumption, investment and the real wage are in first differences, as in Francis and Ramey [2003]. The impulses responses presented in Figure 4, obtained with the same procedure as in Figure 2, show not only that our previous findings are broadly independent of the way variables in the VAR are modelled, but actually they come out stronger with this first difference specification. Technology shocks have a more persistent effect on labor productivity, real wages, consumption and investment, quite likely to be permanent. The 5th percentiles of the distribution of all these variables is now positive for full 20 quarters. Remarkably, a similar behavior is displayed by hours worked, which are now even more likely than in the level specification to increase after a positive technology shock. The median response is always positive, gradually increasing from impact to around 0.4 percent. The probability of an increase in hours worked exceeds 4/5 from the 4th quarter on. Finally, the responses of inflation and the short-term interest rate is indistinguishable from that illustrated in Figure 2.[24]

Galí and Rabanal [2004] raise a further concern on the robustness to the VAR specification, arguing that the reversal in the response of labor inputs to a technology shock documented by Christiano, Eichenbaum and Vigfusson [2003] between the level and difference specification is due to a distortion in their estimated short-run responses, due to the presence of a spurious low frequency correlation between labor productivity growth and per capita hours. Galí and Rabanal [2004] show that the response of labor inputs is always negative when total hours worked are used without a normalization by working age population. Therefore, to make sure that our framework is unaffected by this criticism, we carried out another experiment replacing per capita hours with total hours worked in both the level- and difference- specification VARs. As results are very similar to those presented above, for the sake of brevity we do not report them here. The key finding, however, is that the response of hours worked is more likely to be positive for a longer period than with the benchmark specification.

Overall, these results show that, in stark contrast to the VAR-based literature on technology

[24] Another experiment run with hours, inflation and the interest rate in levels, and all other variables in first differences, yielded very similar results. Namely, the response of hours worked was more persistent and more likely to be positive for a longer period than with the level specification.

shocks, our findings are robust to the level or first difference specification of the VAR. This lends strong support to our view that theory-based sign restrictions are helpful in avoiding a great deal of the subtle specification issues that arise when long run restrictions are used.

4.2.2 Results from the maximum-likelihood estimates

Given that the level specification does not introduce any bias in our procedure, as a further check in this subsection we report results abstracting from the (conjugate) prior on the reduced form parameters of the VAR, and just consider only the uncertainty on the identification of the technology shocks. Precisely, we keep the values of the VAR parameters fixed at their OLS-Maximum Likelihood estimates and draw a large number of candidate impulse response vectors, discarding those that do not satisfy the sign restrictions in Table 2.

This exercise should highlight any bias in favor of estimating a positive response of the labor input potentially introduced in the posterior distribution by our diffuse prior, in case the latter was dominating the data likelihood. Given our interest in impulse responses, it is not immediately clear whether a prior that is diffuse on reduced form coefficients could be actually giving more weights to particular impulse response coefficients.

Figure 5 displays the estimated impulse responses of the variables in our system to a technology shock obtained from the OLS estimates of the VAR in levels and from drawing 50000 candidate impulse vectors from $\mathcal{S}^7$. As before, we report the median (the thick, solid line) and the 5th, 16th, 84th and 95th percentiles (the dashed lines) of the pointwise distribution of the accepted impulse responses.

The key result is as follows. All impulse responses are quite similar to those displayed in Figure 2. Fixing the VAR parameters and abstracting from the uncertainty on their estimation only makes the band between the 5th and the 95th percentiles slightly narrower. This shows that the posterior distribution from which we draw the realizations of the VAR reduced form coefficients is actually quite concentrated around the OLS-ML estimates, mainly reflecting the likelihood. Therefore, the prevailing source of dispersion in our estimated impulse responses clearly reflects the multiplicity of impulse vectors that satisfy our sign restrictions, qualifying as technology shocks. It is thus remarkable that they lead to quite definite conclusions on the response of hours worked to technology shocks.

4.2.3 Subsample stability

In this subsection we briefly discuss subsample stability of our specification. Galí, López-Salido and Vallés [2003] have found that the effects of technology shocks estimated with long-restrictions differ drastically between the two periods before and after Volcker's tenure at the helm of the Federal Reserve System. Precisely, a positive technology shock identified as in Galí [1999] brings about a decline in hours worked in the subsample up to the early 1980's, and a rise afterwards, because of the kind of systematic monetary policy adopted by the Federal Reserve System in the two subperiods. Due to the inclusion of inflation and the short-term interest rate in our VAR, our sample is actually different from those originally used by Galí [1999] and Francis and Ramey [2003], giving relatively more weight to the second sample used by Galí, López-Salido and Vallés [2003]. Here therefore we assess the robustness of our conclusions to the possibility of subsample instability.

Figures 6A and 6B present the estimated impulse responses of the variables in our system to a technology shock for the pre-1979 and post-1983 sample periods respectively, obtained using the same algorithm as in Figure 2.[25] As before, each figure shows the median (the thick, solid line) and the 5th, 16th, 84th and 95th percentiles (the dashed lines) of the pointwise distribution in the indicated subsample.

The following results stand out. First, the qualitative patterns of all variables responses are broadly similar across both periods and to those estimated in the full sample. In particular, hours worked rise in a hump-shaped pattern in both subsamples. Interestingly, this increase appears to be slightly more likely in the early period, in which the 5th percentile is now positive from the 5th to the 12th quarter following the shock. Second, in the late period, the estimated effects of technology appear somehow smaller relative to the earlier period. For instance, the median response of labor productivity is always below 0.4 percent, whereas it close to 0.5 percent in the first few quarters in the earlier subsample. This is consistent with the well-documented drop in aggregate volatility in the last two decades.[26]

This evidence, similar to that obtained by Christiano, Eichenbaum and Vigfusson [2003] with long-run restrictions, is consistent with the view that the responses in the subperiods are the same as

[25]The sample period ranging from 1979:3 to 1982:4 is avoided because of the nonborrowed targeting regime adopted by the Federal Reserve, which induced a significant increases in the volatility of the Federal funds rate (see Bernanke and Mihov [1998]).

[26]See Stock and Watson [2002], among others. Intriguingly, these authors argue that the decrease in volatility is mainly due to smaller, less volatile shocks.

they are for the full sample and there is no break in the response of the interest rate and inflation to technology shocks. In particular, although in the first subsample a drop in the interest rate is slightly more likely as the median response is definitely negative for a couple of quarters, this does not appear sufficient to reject the hypothesis of no sample break in the VAR in more formal way. Nevertheless, even though falling short of such formal results, the crucial finding from our perspective is that inference about the response of hours worked to a technology shock is not affected by subsample stability issues.

4.3 Evidence from other G-7 economies

The estimated impulse responses to a positive technology shock for Japan and (West) Germany up to 20 quarters, obtained with the same procedure as in Figure 2, are presented in Figures 7A to 7B, respectively. Figures 8A to 8B present the implied variance decomposition results at horizons up to 40 quarters. As above, these figures report the median, the 68 and the 90 percent pointwise intervals.

Figures 7A and 7B show a message broadly consistent with that emerging from the U.S. economy. The pattern of responses of output, consumption and investment is similar to that in the U.S. economy. The response of real wages on impact, unrestricted, is positive with more than 0.8 probability in Japan but not in Germany. The median response of hours worked is hump shaped and generally positive in both Germany and, to a lesser degree, in Japan. In the former country it reaches a peak around 3 quarters, remaining positive with a 0.8 probability for several quarters. The effect on labor input now appears rather inconclusive in Japan, however, as the 16th percentile is always negative.

Conversely, the effects of technology shocks on the short-term nominal interest rate and inflation appear to differ across countries. While the median response of the short-term interest rate was basically zero in the U.S., the shock is more likely to bring about a moderate and delayed interest-rate increase in both Japan and, especially, Germany. In the latter country, the change in the interest rate is positive with 0.8 probability in each individual quarter between 1 and 4 years after the shock. The response of inflation is negative in Germany for 1 quarter after impact with more than 4/5 probability. It is marginally positive in both Japan and Germany during the third year after the impact.

The contribution of the technology shocks to aggregate fluctuations was again evaluated by computing the percent of the variance of the k-step ahead forecast error that is accounted for by technology shocks. Figures 8A to 8B presents the variance decomposition results at horizons up to 20 quarters, reporting the median, the pointwise 68 and 90 percent bands.

We see from Figures 8A-8B that technology shocks can explain up to over 50 percent of the variability in labor productivity, output, consumption, investment and real wages up to 5 years in both countries. In Japan, the explained fraction of variability in hours is in each quarter below 40 percent with 4/5 probability, with a median of less than 10 percent only. Conversely, in Germany the 90 percent band includes 40 percent in most horizons.

Finally, turning to nominal variables, Figures 8A and 8B indicate that the contribution of technology shocks to the forecast error variance of inflation and interest rates is higher in the short-run (up to 40-50 per cent) and falls to below 30 per cent in the long run, with the exception of the German short-term interest rate, for which the fraction can be as high as 50 percent even after 4 years.

5 Why are results with sign restrictions different?

In this section we try to account for the reasons why our findings about the behavior of hours worked are different relative to most of the VAR literature using long-run restrictions. We do this by sequentially examining alternative explanations. First, we make sure that our procedure does not have any inherent bias against finding a decline in hours following a technology improvement, if this is what happens in the "true" world. Precisely, we show that it can recover the correct, negative sign of the response of hours worked when applied to simulated time-series generated by a version of our model that is parameterized in such a way that hours fall in response to a technology shock.

Second, we ask whether our results may be due to the fact that our procedure is mixing up technology shocks with other shocks that may bring about a more positive response of hours worked, like monetary policy shocks, investment efficiency shocks and capital-income tax shocks. It should already be clear from our analysis of the theoretical impulse responses in Section 2 that, given the class of DSGE models we consider under our priors on structural parameters, the set of sign restrictions that we impose should allow us to uniquely disentangle (neutral) technology shocks from other shocks. However, here we take a more empirical view, showing that our results are quite robust to controlling for interest rate cuts, changes in capital-income taxes and imposing a positive lower bound on the response of consumption — highly unlikely to occur after an investment efficiency shock.

Finally, after having shown that our findings are not likely to be due to mistaken inference caused by the above sources of misspecification, we argue that differences in results instead reflect, more obviously, differences in the identification strategies. Even when we focus on those structural impulse vectors that explain a large fraction of labor productivity in the long run, we always find that hours worked, regardless of how uncertain their response on impact might be, sharply rise with a hump-shaped pattern. Moreover, this kind of impulse responses that yield dynamic effects similar to those estimated with long-run restrictions are also relatively unlikely. Most structural impulse vectors uncover technology shocks whose long run effects are somehow smaller and less persistent, and bring about an increase in hours worked within the first few quarters.

5.1 Can sign restrictions correctly recover a decline in hours?

In this subsection we examine whether the approach based on sign restrictions is able to detect a contractionary effect on hours worked stemming from a positive technology shock, if this was the true pattern in the data. Given the growing use of sign restrictions to identify different shocks, e.g. monetary or fiscal shocks, this question is of independent interest, as, to the best of our knowledge, it has not been addressed in the literature so far.

In line with a recent pattern in the VAR literature aiming at assessing the ability of a given set of identifying restrictions to recover the true impulse responses when applied to simulated data, we run the following experiment.[27] First, from the set of parameters that are consistent with our sign restrictions, we select a vector associated with a response of hours to a positive technology shock that is always negative for 20 quarters, similarly to the findings in Galí [1999] and Francis and Ramey [2003]. From this economy we then simulate a large number of time series for labor productivity, hours worked, real wages, consumption, investment, inflation and the short-term interest rate. Second, for each realized time series, we estimate a reduced form VAR with 3 lags and apply the above procedure to estimate the effects of technology shocks. Namely, using the VAR OLS-ML estimates we draw a large number of impulse vectors and compute the implied impulse responses to a technology shock, discarding those violating the sign restrictions in Table 2.

Table 3 reports the vector of model's parameters and the processes assumed for the measurement errors. Several of these values are quite standard in the quantitative macro literature.[28] However,

[27]See, among others, Giannone, Reichlin and Sala [2002], Erceg, Guerrieri and Gust [2003], and Chari, Kehoe and McGrattan [2004].

[28]We were unable to use the parameters estimated by Galí and Rabanal [2004] as their model lacks capital accumulation. Indeed, under Galí and Rabanal [2004] estimated means our model with investment imply that in response to a positive technology shock, after an initial fall similar to that reported in their Figure 7, hours worked subsequently sharply rise.

in order to bring about a structural response of hours worked that is always negative, as in some estimated VARs, not only does the model need a relatively high degree of real and nominal rigidities — namely, high values of investment adjustment costs (χ), consumption habits (h), and price/wage probabilities (ξ_p and ξ_w) — but also a reaction function that entails large interest rate hikes in the face of output increases (a large ρ_y). In order to avoid stochastic singularity problems, in the simulations we add measurement errors to each variable in the VAR. The measurement errors are assumed to follow independent AR(1) processes with an autocorrelation parameter equal to 0.5. The variance of their innovations is calibrated so that the standard deviation of the residuals of the VAR estimated on artificial time series is at least as big as that of the corresponding estimates obtained in the actual data.[29]

Figure 9 presents the results from an experiment with 1000 simulations of a length of 200 quarters. For each simulation we drew 500 candidate identifying vectors. The thick solid line is the true impulse response of the variables; the thin line is the median of the pointwise distribution of the estimated impulse responses across simulations, while the dashed lines are its 16th and 84th percentiles.

The key results are as follows. First, the median and both percentiles of the response of hours worked are below zero for the first 4 quarters, thus strongly pointing to the true fact that hours worked decline after a technology improvement. Subsequently the 84th percentile hovers around zero, when the true response of hours rises back to its baseline value, but the median always remains negative. Second, the true impulse response is always below the median and often below the 16th percentile, showing that the estimates are somewhat biased toward zero, as it is usually the case with measurement error. This bias is apparent also for the impulse responses of other variables like investment, inflation and the short-term interest rate, regardless of whether sign restrictions are imposed.[30]

Nevertheless, the crucial result from our perspective is that our approach leads to the correct inference on the response of hours worked and the other variables whose sign is left unconstrained. Therefore, this experiment makes it less likely to believe that our findings may be driven by an

[29] In practice, for the values reported in Table 3, the standard deviations of the VAR residuals of the artificial time series are between 1 and 200 times larger than those of the actual data.

[30] It is worthwhile to note that our VAR may suffer from a subtle form of misspecification, as it is not clear that the reduced form of the artificial time series generated by our model is well represented by a VAR with 3 lags (see Cooley and Dwyer [1998]). Therefore this experiment is actually more demanding that it may seem. For instance, Chari, Kehoe and McGrattan [2004] provides examples in which not only is a VAR facing a similar misspecification strongly biased, but it is not able to recover even the correct pattern and sign of impulse responses with long-run restrictions.

inherent shortcoming of our approach.[31]

5.2 Are sign restrictions confusing different shocks?

In this subsection we turn to the task of investigating whether our results may be due to the fact that our procedure is retrieving not only technology shocks but also other shocks that may bring about a more positive response of hours worked, mixing up their effects. Obvious candidates are monetary policy shocks, investment efficiency shocks and capital-income tax shocks, given the discussion in Section 2.3. From the analysis of the theoretical impulse responses in Section 2.3 clearly emerges that, given the class of DSGE models that we consider under our priors on structural parameters, the set of sign restrictions that we impose allow us to unambiguously disentangle (neutral) technology shocks from other shocks *a priori*.

Precisely, under the uniform prior on parameters reported in Table 1, the effects of a neutral technology shock could be separated from those of both a monetary policy and an investment efficiency shock for the following two reasons. First, an expansionary monetary policy shock would bring about a persistent decline in the interest rate and an increase in inflation, inducing a negative comovement between these two variables. In contrast, they always move in the same direction on impact following a technology shock as shown in Section 2.3. Second, while both investment and consumption rise following a shock to total factor productivity that boosts current output, they will tend to comove negatively in response to an investment-specific shock that does not shift the current production function, with consumption declining. The same reasoning applies to a negative shock to — a fall in — the capital-income tax, which also increases the cost of current consumption relative to future consumption (investment), leaving current production possibilities unaffected.[32]

However, our goal here is to go beyond these theoretical results, and assess the robustness of our findings more broadly. For instance, it is possible to write models in which a monetary expansion brings about a temporary increase in inflation because of cost channel effects, as in Barth and Ramey [2002]. Likewise, interactions between real and nominal frictions, and particularly systematic

[31] We also run experiments under a parameterization consistent with a positive, true response of hours, as the median in Figure 2, and reached very similar results.

[32] Importantly, we can also rule out confusion with price markup shocks, which according to Galí and Rabanal [2004] estimates play an important role in driving the procyclicality of hours worked. Under the prior in Table 1, this kind of shocks implies that the difference between labor productivity and the real wage be persistently negative, whereas it is positive, at least on impact, after a positive technology shock. When we add the latter requirement to the restrictions in Table 2, the estimated impulse responses are virtually indistinguishable from those reported in Figure 2.

monetary policy, different from those we assumed in Section 2, may trigger an increase in consumption in response to an investment-specific shock.

Therefore, in order to address these concerns we carried out the following two experiments. First, in order to unequivocally rule out confusion with monetary policy shocks we redid our empirical analysis assuming the further restrictions that after the shock the nominal interest be positive. Second, we checked the sensitivity of our inference on the behavior of hours to the requirement of a large and positive bound on the response of consumption, and to controlling for capital-income tax changes. Again, across all these experiments our results turn out to be broadly unaffected, thus confirming their robustness beyond the narrower validity of the assumptions underlying our analysis.

Monetary policy shocks. In our first experiment, we complemented the restrictions in Table 2 with the requirement that the interest rate be positive for the first 2 quarters following the shock. This way it should be very unlikely that our identification strategy mistakenly picks expansionary monetary policy shocks for technology shocks.

Figure 10 presents the relevant results, again reporting the 5th, 16th, 50th, 86th and 95th percentiles of the point by point distribution of the impulse responses. It is clear that the impulse responses are very similar to those depicted in Figure 2 with no restrictions on the short-term interest rate — obviously barring the latter's response. In particular, hours worked, if anything, are slightly more likely to increase immediately under this specification, as the 16th percentile hovers very close to zero for the first 10 quarters.

This evidence has at least two noteworthy implications. Not only does it strongly support the contention that our identification strategy does not mix up technology and monetary policy shocks, but it also suggests that our findings are difficult to rationalize in terms of other kinds of shocks — like an investement-specific technology shock — accompanied by an expansionary monetary policy stance that makes their effects look similar to those of technology shock.[33]

Shocks to the consumption-investment transformation rate. Notwithstanding the above observation, we carried out an experiment aimed at uncovering a possible influence on our results of disturbances affecting the rate of transformation between consumption and investment. In particular we added to the benchmark list of restrictions the requirement that consumption be not only positive

[33] We also run an experiment requiring, in addition to the restrictions in Table 2, that inflation and the interest rate have the same sign for 2 quarters after the shock, as prescribed by the model with nominal rigidities. The results of this experiment, available upon request, confirm and actually even strengthen our findings.

for 5 quarters, but also larger than the 16th percentile of its estimated response reported in Figure 2. The idea is that a relatively large response of consumption is very unlikely to be consistent with an investment-efficiency shock.

The results, reported in Figure 11 with the usual format, namely displaying the 5th, 16th, 50th, 86th and 95th percentiles of the point by point distribution of the impulse responses, are again in broad support of our overall findings. Effectively, requiring a more pronounced positive response of consumption makes the increase in hours even larger. The 5th percentile is now positive from the 5th to the 10th quarter. Moreover, the responses of the other variables are barely affected, especially those of investment and the nominal short-term interest rate. In light also of the above evidence on the quite limited role that systematic monetary plays in shaping our results, if our approach was confusing different kinds of technology shocks with opposite effects on hours worked, the stronger response of consumption would have to be associated with a more negative response of hours worked, rather than a more positive one.[34]

Our last exercise was to examine the robustness of our results to capital-income tax shocks. Following Francis and Ramey [2003] we tackled this problem this way. We constructed a series for the capital tax rate shock as in Jones [2002], and included it as an exogenous variable when estimating the reduced form VAR, before imposing the sign restrictions in Table 2. Since our results are again unaffected, to save on space we do not report them here. We also computed the correlation between our estimates of technology shocks in the U.S., across all identifications, and the AR(1) innovations to the series of the capital tax rate, interpreted by Jones [2002] as tax shocks. This correlation is not significantly different from zero.

5.3 Are long-run restrictions consistent with sign restrictions?

As mentioned above, in contrast to standard structural VAR analyses, relying on just- or over-identifying restrictions to estimate a unique impulse vector that maps reduced form residuals into structural shocks one-to-one, our procedure yields a number of impulse vectors that have a structural interpretation. In this light, a useful starting point to understand the above findings is to ask whether among those structural impulse vectors there is any subset that can be interpreted as consistent with long-run restrictions.

Obviously, in principle there should be only one, if any, impulse vector that accounts for all

[34]We also verified that including consumption durables in investment and leaving only nondurables in consumption proper did not change our findings. Results are available upon request.

variation in labor productivity in the — however defined — "long run". Nevertheless, an advantage of our approach is that it allows to assess if quantitative changes in the amount of variation in labor productivity explained at a given long horizon are reflected in qualitative changes in impulse responses. Therefore, among the set of structural impulse vectors that satisfy our sign restrictions, we selected those that account for over 70 percent of the forecast error variance of labor productivity after 10 years— i.e., the "long run" in this exercise is meant to be 40 quarters — rather than focusing on just one of them.[35] Given the results in Section 4.2.2, for simplicity the candidate impulse vectors were computed with the parameters of the reduced form VAR for the U.S. held constant at their OLS-ML estimates.

Figure 12 presents the usual five percentiles of the point by point distribution of the impulse responses selected this way. The key results are as follows. First, the distributions are generally much less dispersed than those reported in Figure 5, for less than 5 percent of them exceed the 70 percent threshold, as should also be clear from the findings on variance decomposition in Section 4.1. However, for labor productivity, real wages, investment, inflation and the interest rate, the dispersion regarding the effects on the first couple of quarters is still substantial. The short-run effects on consumption and hours are instead rather tightly estimated. Therefore, the uncertainty does not seem to depend on whether a sign restriction is imposed.

Second, the dynamic effects of the shock on labor productivity, real wages, output, consumption and investment appear indisputably permanent, similarly to those estimated with long-run restrictions. All these variables are positive on impact and then rise reaching a new long run level. Output, consumption and investment, however, display a marked hump-shaped pattern, peaking around 10 quarters after the shock, before converging from above to the new level.

Third, the impact response of the unrestricted variables, i.e. hours worked, inflation and the interest is now clear-cut: they all fall. Inflation and the short-term interest rate remain negative for 3 and 10 years, respectively. By contrast, hours worked strongly rise with a hump-shaped pattern, becoming positive after 5 quarters and peaking around 3 years at roughly 0.4 percent, to return to the baseline value only very slowly. Most importantly, this increase is such that the correlation at business cycle frequencies between the technology component of hours worked and output in the data, extracted using the band pass filter of Baxter and King [1999], is positive and significant, on average equal to 0.60. This result is clearly in contrast with the findings of Galí and Rabanal [2004]

[35] Results below are reasonably robust to changes in the 40 quarters horizon or the 70 percent variance decomposition threshold.

in a similar exercise based on long-run restrictions (see Figure 3 in their paper).

Therefore, our procedure recovers a subset of impulse responses implying dynamic effects that are very similar to those obtained by means of long-run restrictions. Nevertheless, in line with the results in Christiano, Eichenbaum and Vigfusson [2003], these permanent shocks still lead to a significant increase in hours, though with a few quarters delay.[36] However, a level specification of hours cannot be all the story, as should be clear from Figure 4, unquestionably showing that our results are independent of whether the VAR is estimated in levels or first differences. There is another important message that stems from the impulse vectors identified by our procedure and *not included* in Figure 12. Across all the identification schemes satisfying the sign restrictions, those associated with the large, permanent effects reported in the figure account only for a fraction, though important, of all possible ones. The vast majority of structural impulse vectors imply that a positive technology shock has somehow smaller and less persistent effects in the long run, but brings about an increase in hours worked in the first few quarters. This finding is more in line with the RBC tradition, in which technology shocks are usually assumed to be very persistent but trend stationary. Interestingly, the different initial effect on hours worked may be easily rationalized with the different size and persistence of the two types of shocks and the implied different wealth effects on labor supply.

Overall, the key result from our perspective is that we never find a structural impulse vector consistent with sign restrictions such that technology shocks explain 100 percent of the long run forecast error of labor productivity. The maximum fraction explained never exceeds 85 percent at the 10 years horizon. This suggests that identifying assumptions arising from long run restrictions, among which atheoretical assumptions play a crucial role, are not consistent with sign restrictions, that have firm underpinnings in economic theory. It thus may well be that, as argued by Uhlig [2003], other shocks contribute to long run movements in labor productivity, thus casting some doubts on the ability of long run restrictions to isolate the effects of neutral technology shocks.

[36] As discussed by Shapiro and Watson [1988], the identifying assumption that technology shocks are the only source of the unit root in labor productivity effectively is equivalent to restricting the other variables to enter the labor productivity equation in first-differences (if assumed to be trend stationary) or double-differences (if difference stationary). In turn, the use of matrix methods implies that the equation is estimated with instrumental variables, using lags of all the variables as instruments. Results are thus likely to be sensitive to weak instruments problems and lead to structural conclusions that are heavily dependent on the set of instruments used, namely on the specification and number of the other variables included in the VAR.

6 Concluding remarks

This paper identifies technology shocks in VAR models of the United States, Japan and Germany by means of restrictions on the sign of impulse responses, derived from an explicit, uniform prior on the parameters of a class of dynamic general equilibrium models. Technology shocks are found to entail a significant and persistent increase in labor productivity, real wage, consumption, investment and output; hours worked increase with a humped-shape pattern. In addition, the view that technology shocks play a substantial role in accounting for business cycle fluctuations cannot be rejected, although these shocks leave unexplained most of the variation in hours worked.

This paper has focused on the estimation of impulse responses and variance decompositions to technology shocks. However, a natural question to ask is whether it would possible to draw implications on the parameterizations that are more likely to be associated with relevant features of the density of the estimated impulse responses. This is important as it could shed light on key aspects of the internal propagation mechanism of DSGE models, e.g., whether the fact that consequences of a technology shock resemble those in an RBC model might in reality reflect that the actual economy has various nominal frictions, and monetary policy has successfully mitigated those frictions.

As the exercise was started out by motivating restrictions on impulse responses with a set of model economies, a clear advantage of its approach is the clear link between structural impulse responses and theoretical properties of the models. Therefore, if the (highly nonlinear) mapping from the model's parameter space into impulse responses could be inverted, it would be possible to map the posterior density of impulse responses back into posterior densities of structural parameters. There are, however, several nontrivial aspects of this task, due to the fact that we would be trying to form our inference from a vector-valued function of a vector of parameters, with the dimensionality of both vectors quite high. Hence, an interesting issue for future research would be to compute the likelihood of a vector of impulse responses and estimate the posterior distribution of the parameters of the underlying DSGE model, perhaps suitably adapting methods such as the Sequential Monte Carlo algorithm of Fernández-Villaverde and Rubio-Ramírez [2004].

References

[1] Basu, S., J. G. Fernald and M. S. Kimball [1998], "Are technology improvements contractionary?", International Finance Discussion Paper, No. 625.

[2] Barth, M. J. and V. A. Ramey [2002], "The Cost Channel Of Monetary Transmission", *NBER Macroeconomic annuals 2001*, Cambridge, Mit Press, pp. 199-240

[3] Baxter, M. and R. G. King [1999], "Measuring business cycles: approximate band-pass filters for economic time series", *Review of Economics and Statistics*, Vol. 81, No. 4, pp. 575-593.

[4] Bernanke, B. and I. Mihov [1998], "Measuring monetary policy", *Quarterly Journal of Economics*, Vol. 113, No. 3, pp. 869-902.

[5] Bils, M. and P. J. Klenow [2002], "Some evidence on the importance of sticky prices", NBER Working Paper, No. 9069.

[6] Canova, F. [2002], "Validating monetary DSGE models through VARs", CEPR Discussion Paper, No. 3442.

[7] Canova, F. and G. De Nicoló [2002], "Monetary disturbances matter for business cycle fluctuations in the G7", *Journal of Monetary Economics*, Vol. 49, No. 6, pp. 1131-1159.

[8] Chari, V. V., P. J. Kehoe and E. McGrattan [2004], "Are Structural VARs Useful Guides for Developing Business Cycle Theories", mimeo, Federal Reserve Bank of Minneapolis.

[9] Christiano, L. J. and M. Eichenbaum [1992], "Current Real Business Cycle Theories and Aggregate Labor Market Fluctuations", *American Economic Review*, Vol. 82, No. 3, pp. 430-50.

[10] Christiano, L. J., Eichenbaum, M. and C. Evans [2003], "Nominal rigidities and the dynamic effects of a shock to monetary policy", mimeo, Northwestern University.

[11] Christiano, L. J., Eichenbaum, M. and R. Vigfusson [2003], "What happens after a technology shock?", mimeo, Northwestern University.

[12] Clarida, R., Galí, J. and M. Gertler [2000], "Monetary policy rules and macroeconomic stability: evidence and some theory", *Quarterly Journal of Economics*, Vol. 155, No. 1, pp. 147-180.

[13] Coogley, T. and J. M. Nason [1994], "Testing the implications of long-run neutrality for monetary business cycle models", *Journal of Applied Econometrics*, Vol. 9, S37-S70.

[14] Cooley, F., T. and E. C. Prescott [1995], "Economic growth and business cycle", in F., T., Cooley, ed. Frontiers of Business Cycle Research, Princeton: Princeton University Press.

[15] Cooley, F., T. and M. Dwyer [1998], "Business cycle analysis without much theory. A look at structural VARs", *Journal of Econometrics*, Vol. 83, pp. 57-88.

[16] Cogley, T. and T., J. Sargent [2003], "Drifts and volatilities: monetary policies and outcomes in the post-WWII U.S.", mimeo.

[17] Erceg, Christopher J., Luca Guerrieri, and Christopher Gust [2004], "Can long run restrictions identify technology shocks?", Federal Reserve Board, mimeo.

[18] Estima [2000], "RATS User's Guide".

[19] Faust, J. and E. M. Leeper [1997], "When do long-run identifying restrictions give reliable results?", *Journal of Business and Economic Statistics*, Vol. 15, No. 3, pp. 345–353.

[20] Faust, J. [1998], "The robustenss of identified VAR conclusions about money", *Carnegie-Rochester Series on Public Policy*, Vol. 49, pp. 207-244

[21] Fernández-Villaverde, J. and J., F. Rubio-Ramírez [2004], "Estimating dynamic equilibrium economies: linear versus nonlinear likelihood", mimeo, University of Philadelphia.

[22] Francis, N. and V. Ramey [2003], "Is the Technology-Driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited", mimeo, University of California, San Diego.

[23] Fisher, J. D. M. [2002], "Technology shocks matter", Working Paper Federal Reserve Bank of Chicago, No. 2002-14.

[24] Galí, J. [1999], "Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations?", *American Economic Review*, Vol. 89, No. 1, pp. 249–271.

[25] Galí, J., J. D. López-Salido and J. Vallés [2003], "Technology shocks and monetary policy: assessing the Fed's performance", *Journal of Monetary Economics*, Vol. 50, pp. 723–743.

[26] Galí, J. and P. Rabanal [2004], "Technology shocks and aggregate fluctuations: How well does the RBC model fit postwar U.S. data?", forthcoming in *NBER Macroeconomic annuals 2004*.

[27] Giannone, D., Reichlin, L. and L. Sala [2002], "VARs, common factors and the empirical validation of equilibrium business cycle models", mimeo, ECARES, Université Libre de Bruxelles and IGIER - Universitá Bocconi.

[28] Greenwood, J., Z. Hercowitz and G. W. Huffman [1988], "Investment, Capacity Utilization, and the Real Business Cycle", *American Economic Review*, Vol. 78, No. 3, pp. 402-417.

[29] Greenwood, J., Z. Hercowitz and P. Krusell [2000], "The Role of Investment-Specific Technical Change in the Business Cycle", *European Economic Review*, Vol. 44, pp. 402-417.

[30] Hamilton, J. D. [1994], Time Series Analysis, Princeton: Princeton University Press.

[31] King, R. and S. T. Rebelo [1999], "Resuscitating the Real Business Cycle," in J. Taylor and M. Woodford, eds., Handbook of Macroeconomics, Amsterdam: North-Holland.

[32] Kydland, F., E. [1984], "Labor force heterogeneity and the business cycle", *Carnegie-Rochester Conference Series on Public Policy*, Vol. 21, pp. 173-208.

[33] Kydland, F., E. [1995], "Business cycles and aggregate labor market fluctuations", in T. F. Cooley Frontiers of Business Cycle Research, Princeton: Princeton University Press.

[34] Kydland, F., E. and E. C. Prescott [1982], "Time to build and aggregate fluctuations", *Econometrica*, Vol. 45, pp. 329-359.

[35] Jones, J. B., [2002], "Has fiscal policy helped stabilize the postwar U.S. economy?", *Journal of Monetary Economics*, 49, pp. 709-746.

[36] Lubik, T.A. and F. Schorfheide [2004], "Testing for indeterminacy: an application to U.S. monetary policy", *American Economic Review*, Vol. 94, No. 1, pp. 190-217.

[37] McGrattan, E.R. [1994], "The macroeconomic effects of distortionary taxation", *Journal of Monetary Economics*, Vol. 33, pp. 573-601.

[38] McGrattan, E., R. [2004], Comment on Galí, J. and P. Rabanal "Technology shocks and aggregate fluctuations: How well does the RBC model fit postwar U.S. data?", Research Department Staff Report No. 338, Federal Reserve Bank of Minneapolis; forthcoming in *NBER Macroeconomic annual 2004*.

[39] Phillips, P. C. B. [1991], "To criticize the critics: an objective Bayesian analysis of stochastic trends", *Journal of Applied Econometrics*, Vol. 6, pp. 333-364.

[40] Prescott, E.C. [1986], "Theory ahead of business-cycle measurement", *Carnegie-Rochester Conference Series on Public Policy*, Vol. 25, pp. 11-44.

[41] Ramey, V. [2004], Comment on Galí, J. and P. Rabanal "Technology shocks and aggregate fluctuations: How well does the RBC model fit postwar U.S. data?", forthcoming in *NBER Macroeconomic annual 2004*.

[42] Shapiro, M.D. and M.W. Watson [1988], "Sources of business cycle fluctuations,", *NBER Macroeconomics annual 1988*, pp. 111-48.

[43] Shea, J. [1998], "What do technology shocks do?", NBER Working Paper, No. 6632.

[44] Sims, C., A. and T. Zha [2004], "Were there regime switches in US monetary policy", mimeo.

[45] Smets, F. and R. Wouters [2003], "An estimated DSGE model of the euro area", *Journal of the European Economic Association*, Vol. 1, No. 5, pp. 1123-1175.

[46] Stock, J.H. and M.W. Watson [2002], "Has the business cycle changed and why?", *NBER Macroeconomics annual 2002*, pp. 159-218.

[47] Uhlig, H. [2001], "What are the effects of monetary policy on output? Results from an agnostic identification procedure", Tilburg University, Center for Economic Research Discussion Paper, No. 28.

[48] Uhlig, H. [2003], "Do technology shocks lead to a fall in total hours worked?", *Journal of the European Economic Association*, Vol. 2, No. 2-3, pp. 361-371.

Appendix: description of the data

United States

Labor productivity: index of output per hour, non-farm business sector (Bureau Labor Statistics, BLS).

Hours worked: index of total hours worked, non-farm business sector (BLS).

Real wage: real hourly compensation, non-farm business sector (BLS).

Consumption: personal consumption expenditures, billions of chained (1996) dollars (Bureau Ecopnomic Analysis, BEA).

Investment: gross private capital formation, billions of chained (1996) dollars (BEA).

Short-term interest rate: Federal funds rate (Federal Reserve Bank of St. Louis).

Inflation: quarterly changes in the implicit GDP deflator (BEA)

Japan

Labor productivity: ratio between private real GDP (OECD) and total hours worked in non-agricultural private business (source International Labor Office, ILO, for weekly hours worked and Bank for International Settlements, BIS, for employment of employees).

Real wage: wage rates in non-agricultural economy (BIS) deflated with the implicit GDP deflator (OECD).

Consumption: private consumption in 1995 yen (OECD).

Investment is gross private capital formation in 1995 yen (OECD).

The series for private consumption and investment in 1995 base are available only from 1980. For the period before the series are constructed using the growth rates from the series in 1990 base.

The short-term interest rate is the 3-month money-market repo rate (BIS).

Inflation: quarterly changes in the implicit GDP deflator (BIS).

West Germany

Labor productivity: gross domestic product per man-hour at 1991 prices (BIS).

Total hours worked: product of weekly hours (source ILO) and employment of employees (BIS).

Real wage: nominal hourly compensation in private business (BLS) deflated with the implicit GDP deflator (BIS).

Consumption: private consumption in 1991 DM (BIS). Investment: gross private fixed capital formation in 1991 DM (BIS).

The short-term interest rate is the 3-month money-market rate (BIS).

Inflation: quarterly changes in the implicit GDP deflator (BIS).

Table. 1 Parameters ranges

parameter	low	up	mean
b	0.985	0.995	0.99
σ_c	1.0	10.0	5.50
σ_l	0.0	10.0	5.0
h	0.0	0.8	0.4
χ	0.0	5.0	2.5
ξ_p	0.0	0.8	0.405
γ_p	0.0	1.0	0.5
ξ_w	0.0	0.8	0.405
γ_w	0.0	1.0	0.5
λ_w	0.0	1.0	0.5
ψ	0.0	50.0	25.0
ρ_r	0.0	0.99	0.495
ρ_y	-0.25	0.25	0.0
ρ_π	1.1	2.0	1.55
ρ_z	0.75	0.999	0.8495
ρ_i	0.75	0.999	0.8495

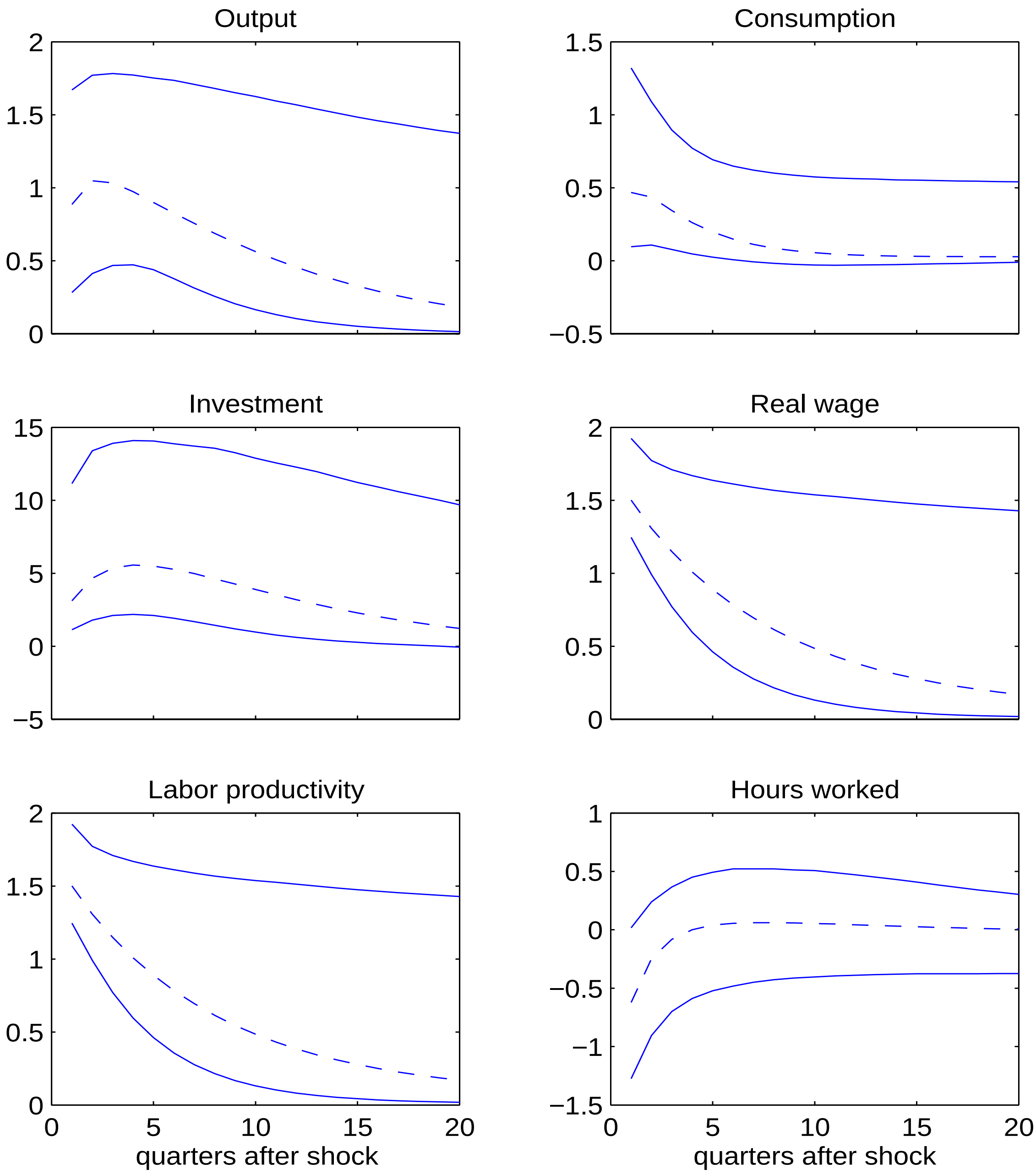
Table. 2 Sign restrictions on VAR variables

Variable	Horizon in quarters
$lp_k \geq 0$	$k = 1, ..., 20$
$w_k \geq 0$	$k = 3, ..., 20$
$i_k \geq 0$	$k = 1, ..., 10$
$y_k \geq 0$	$k = 1, ..., 10$
$c_k \geq 0$	$k = 1, ..., 5$
$h_k \lesseqgtr 0$	$k = 1, ..., 20$
$\pi_k \lesseqgtr 0$	$k = 1, ..., 20$
$r_k \lesseqgtr 0$	$k = 1, ..., 20$

Table. 3 Parameters for generating simulated time series

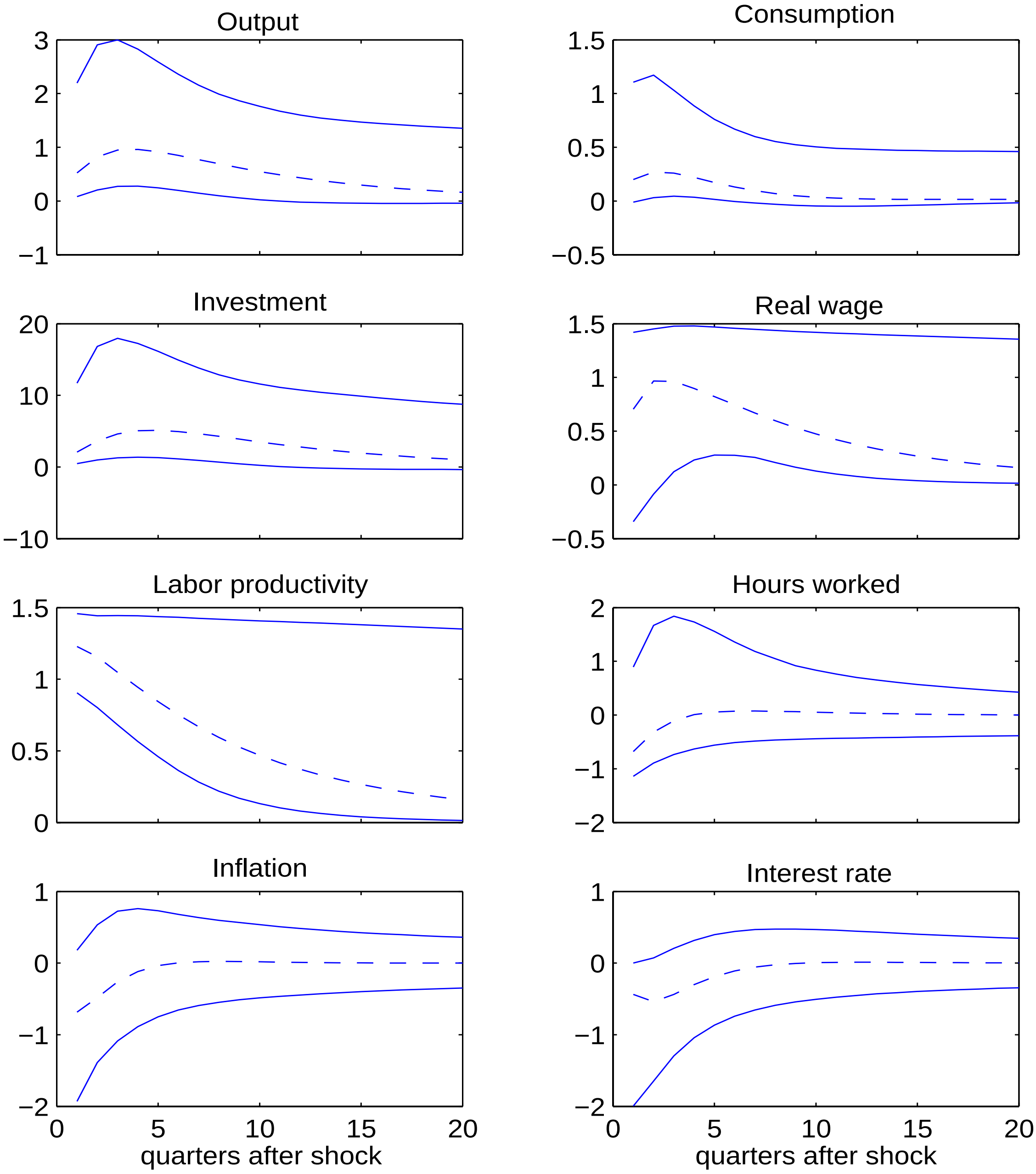
Model's parameters		
α		0.33
δ		0.025
β		0.99
σ_c		1.00
σ_l		0.80
h		0.80
χ		5.00
ξ_p		0.80
γ_p		0.50
ξ_w		0.80
γ_w		0.50
λ_w		0.20
ψ		0.005
ρ_r		0.75
ρ_y		0.20
ρ_π		1.45
ρ_z		0.95
σ_z		0.003
trend		1.004
Measurement error		
serial correlation		0.50
	lp	$0.5 * 10^{-4}$
	w	$0.5 * 10^{-4}$
	h	$0.5 * 10^{-4}$
standard deviation	i	$3.5 * 10^{-4}$
	c	$0.5 * 10^{-4}$
	π	$0.2 * 10^{-5}$
	r	$0.2 * 10^{-5}$

Fig. 1A Impulse responses to positive technology shock: RBC prior



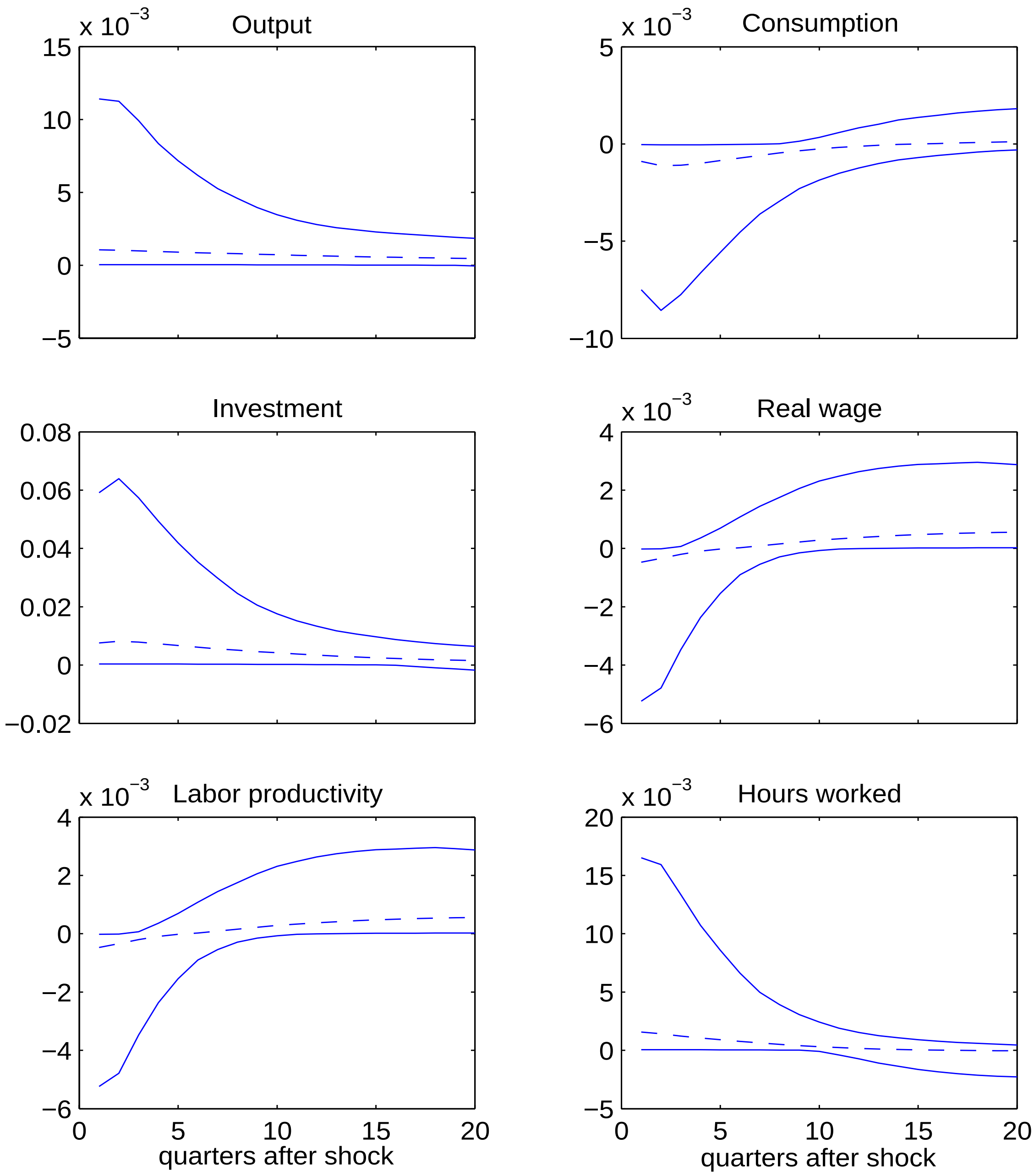
– – median — 2.5, 97.5 percentiles

Fig. 1B Impulse responses to positive technology shock: NR prior



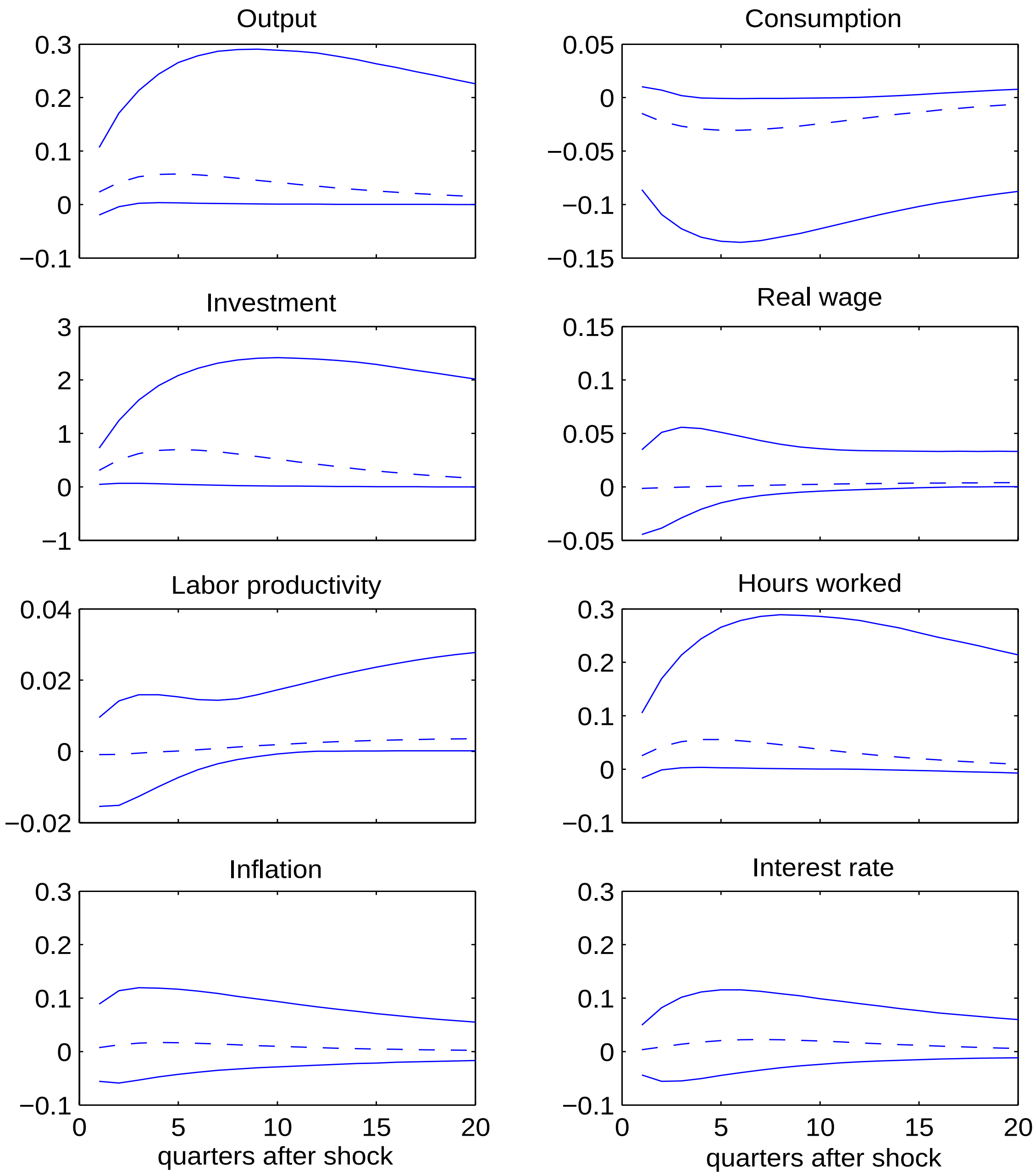
– – median — 2.5, 97.5 percentiles

Fig. 1C Impulse responses to a positive investment efficiency shock: RBC prior



– – median — 2.5, 97.5 percentiles

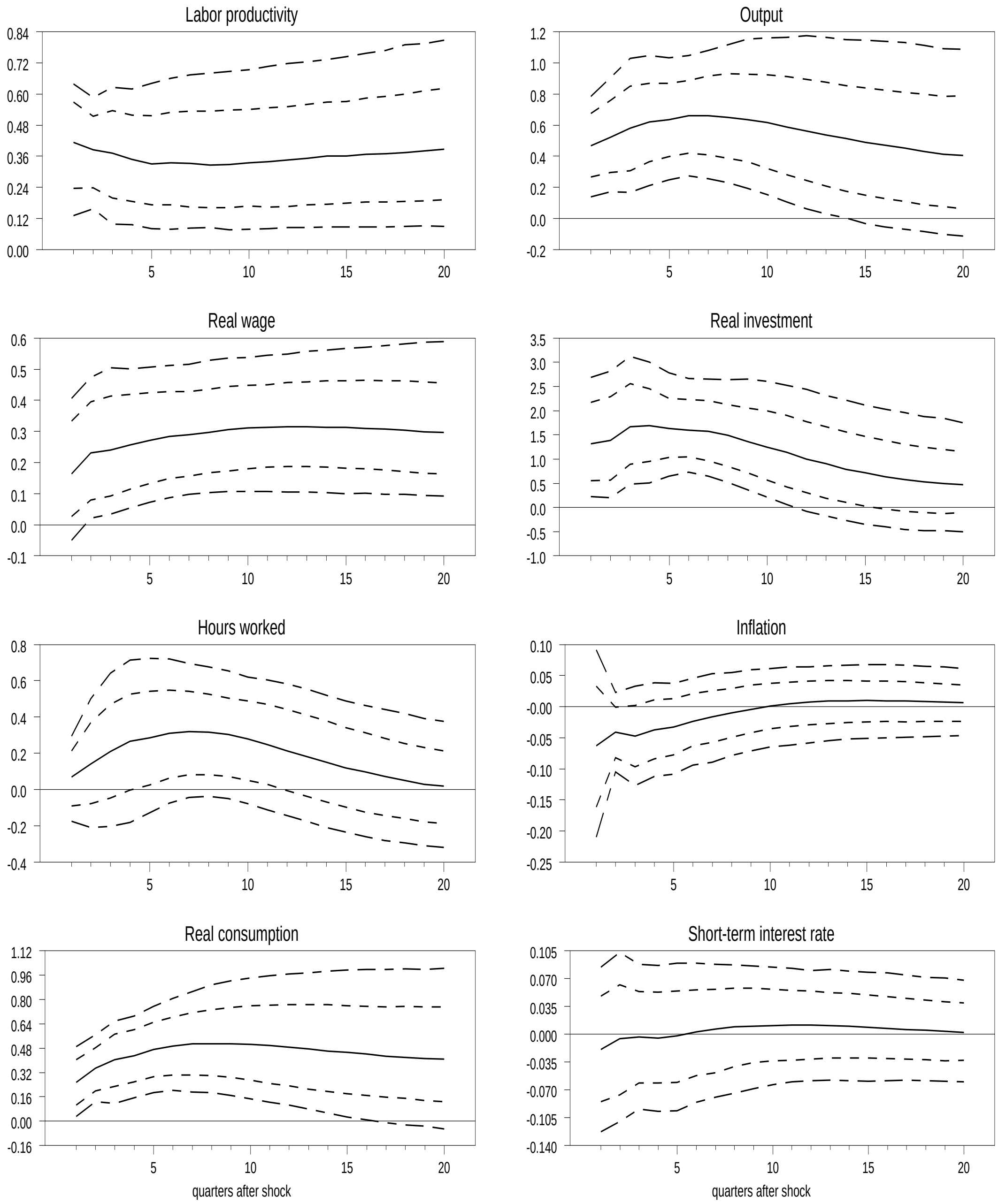
Fig. 1D Impulse responses to a positive investment efficiency shock: NR prior



– – median — 2.5, 97.5 percentiles

Fig. 2 Impulse responses to positive technology shock: United States

Benchmark specification[a]

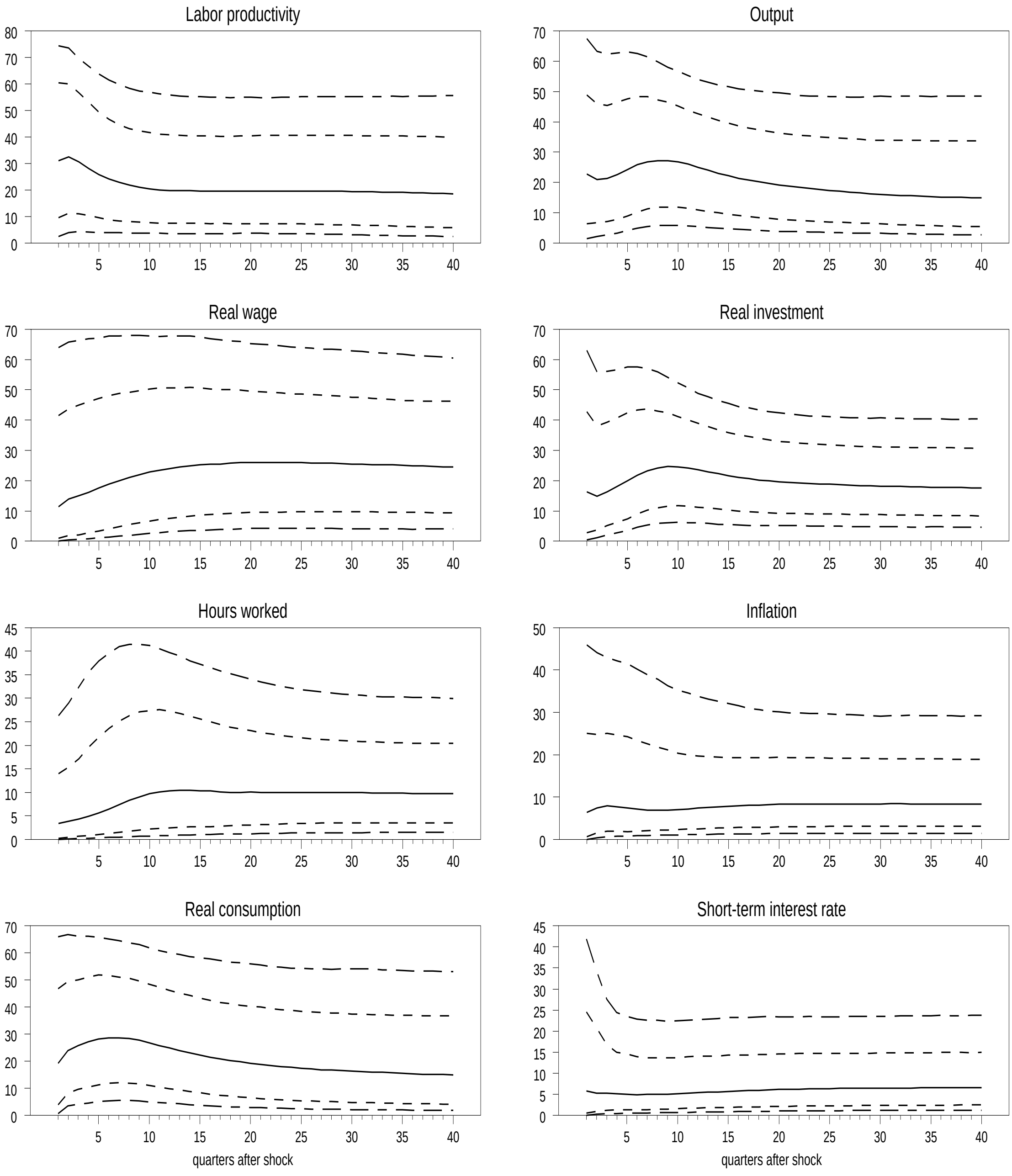


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a]All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 1953:1-2003:4.

Fig. 3 Contribution of technology shocks to forecast variance: United States

Benchmark specification[a]

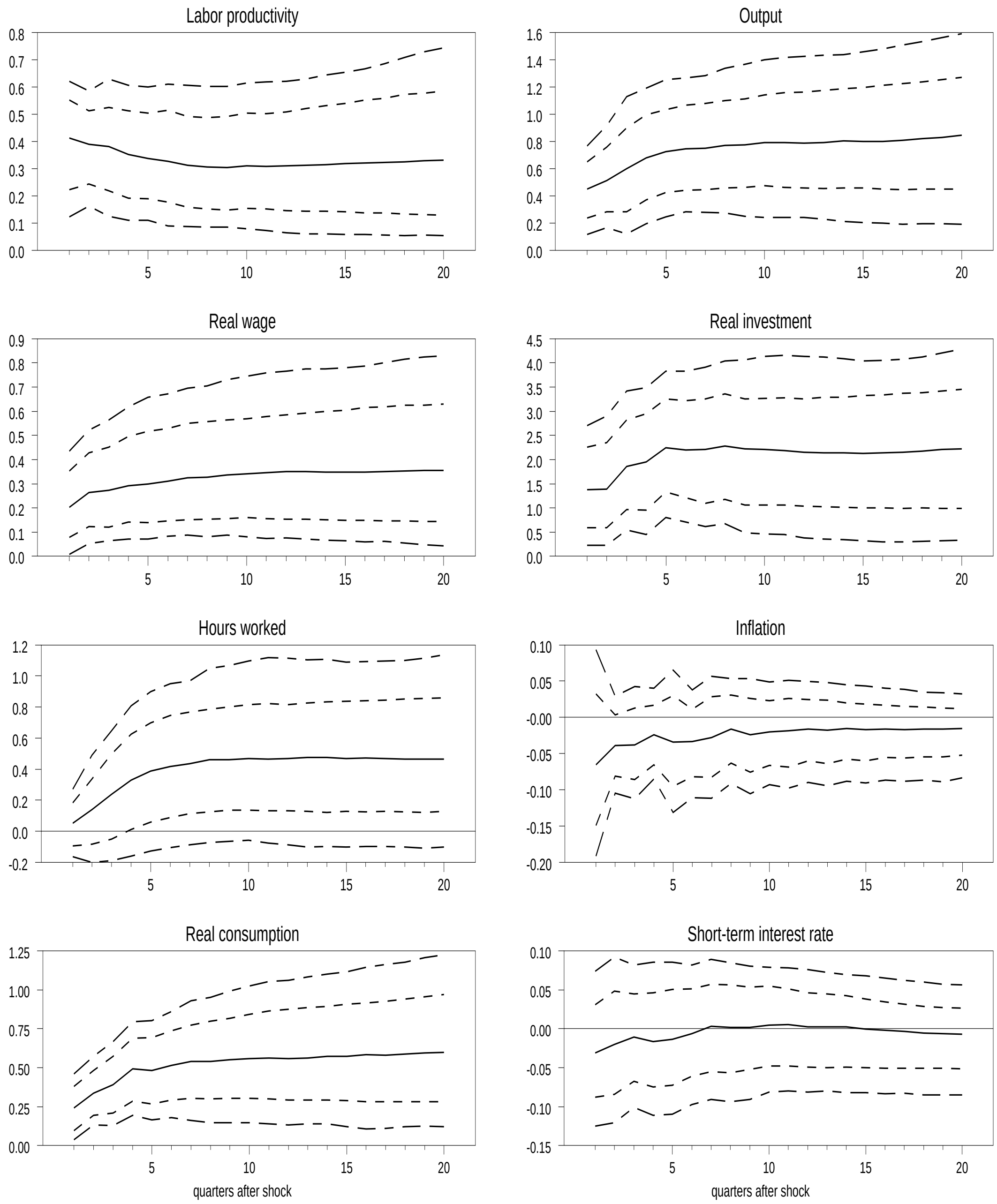


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a]All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 1953:1-2003:4.

Fig. 4 Impulse responses to positive technology shock: United States

Difference specification[a]

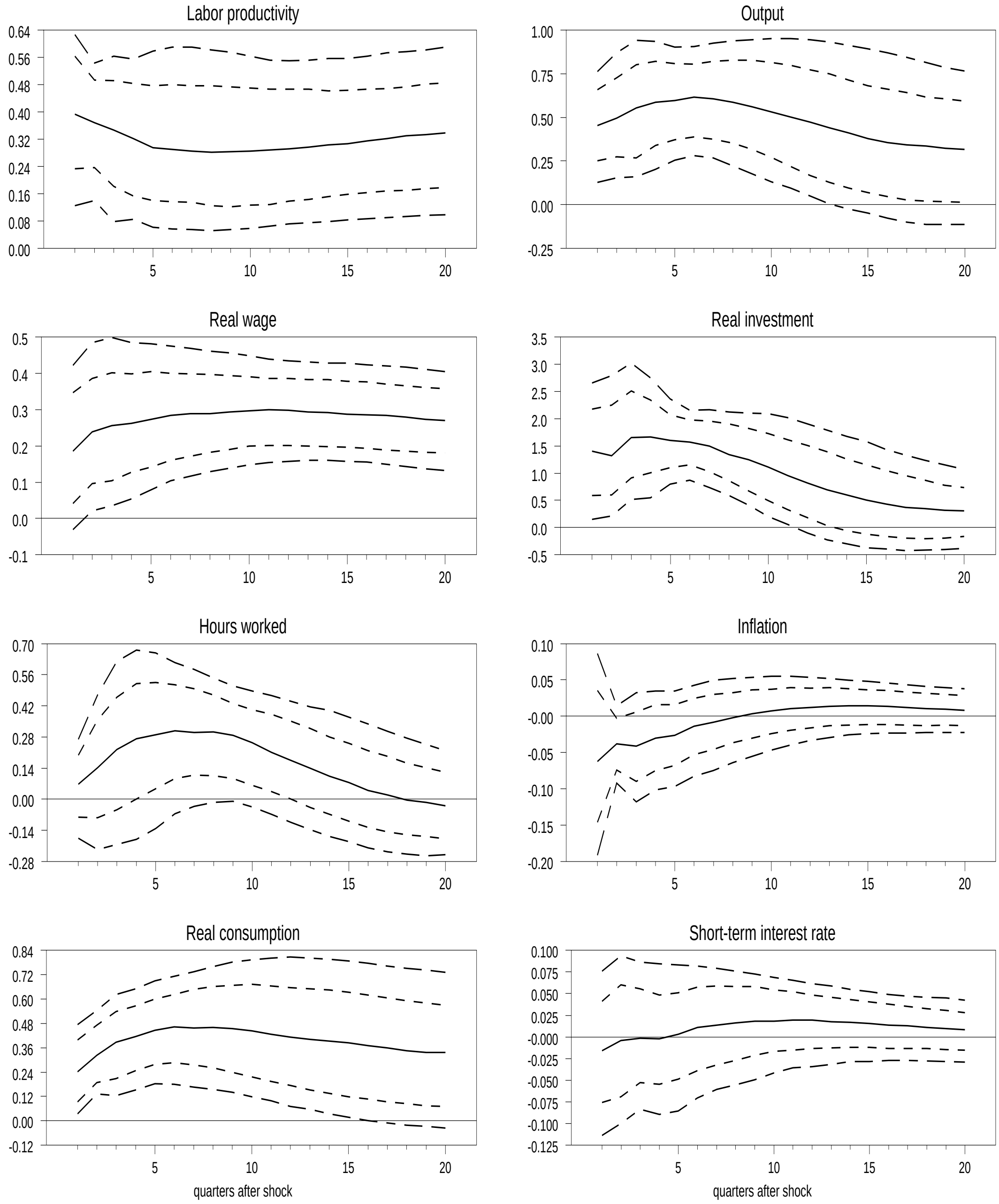


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a] All variables, except the Federal funds rate and inflation, are in first differences. Assumed sign restrictions are reported in Table 2. Sample period is 1953:1-2003:4.

Fig. 5 Impulse responses to positive technology shock: United States

The effect of identification uncertainty only[a]

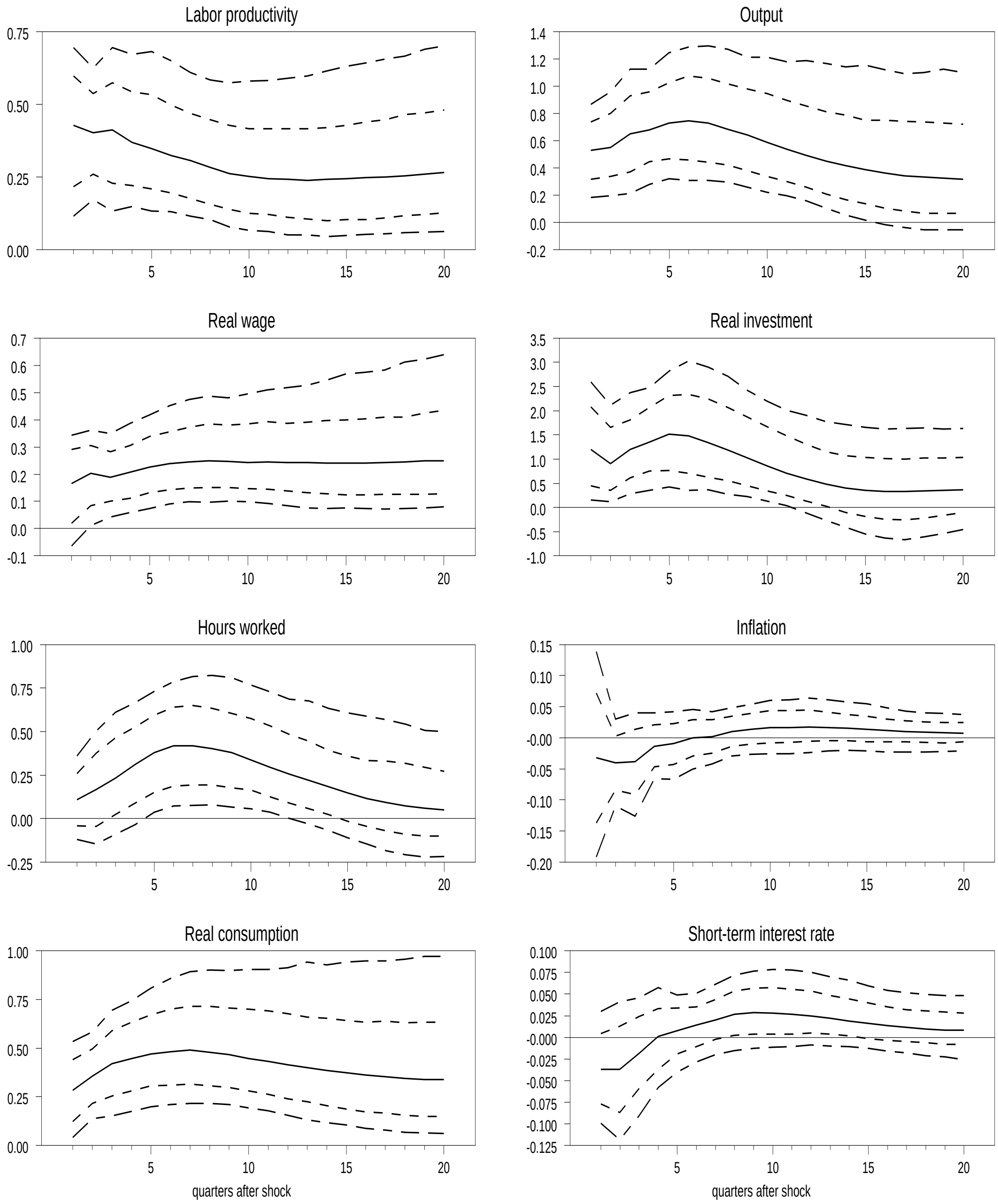


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a]All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 1953:1-2003:4. The reduced form of the VAR and the covariance matrix are fixed at their OLS-ML estimates.

Fig. 6A Impulse responses to positive technology shock: United States

Pre-1979:2 period[a]

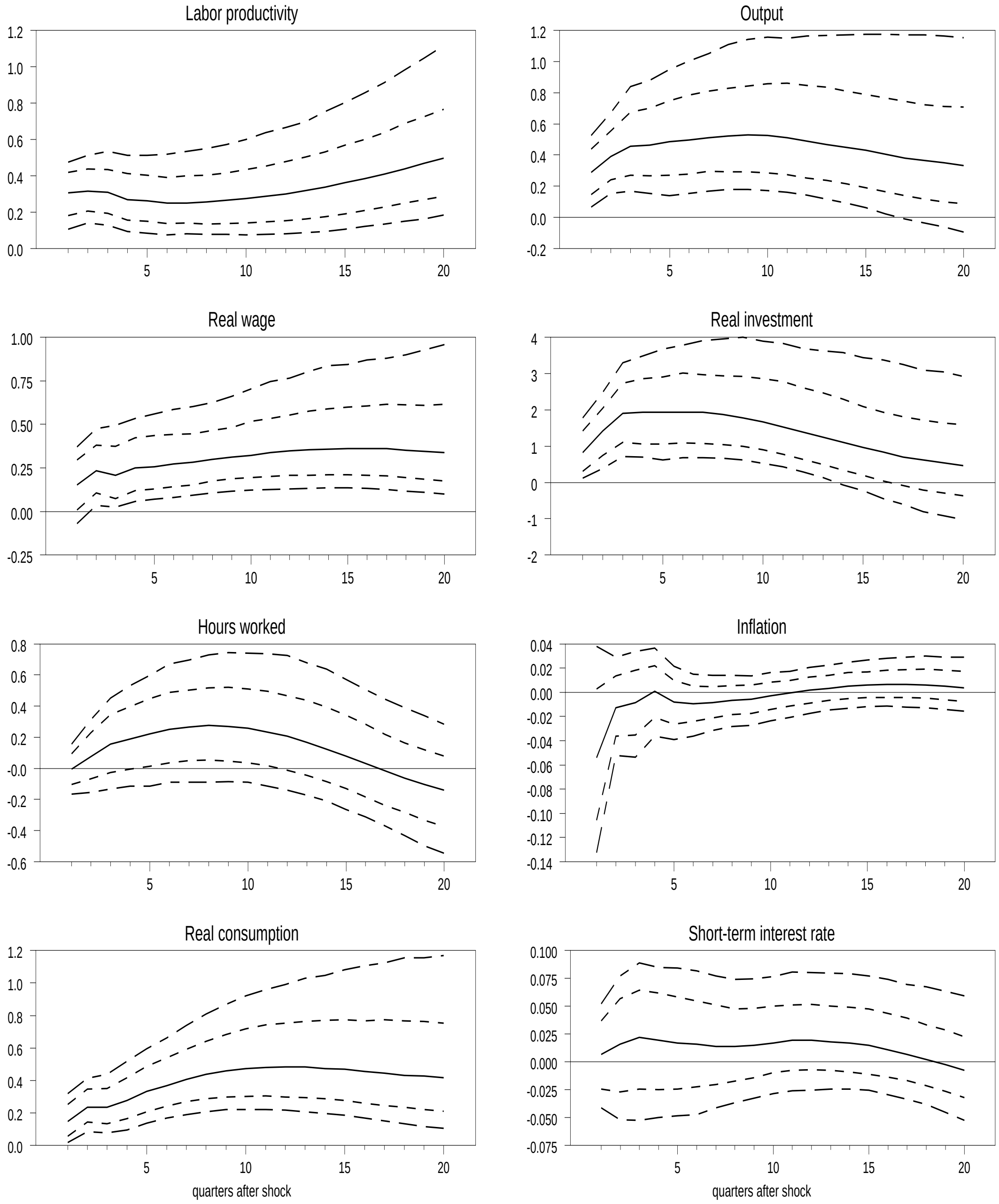


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a] All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 1953:1-1979:2.

Fig. 6B Impulse responses to positive technology shock: United States

Post-1983:1 period[a]

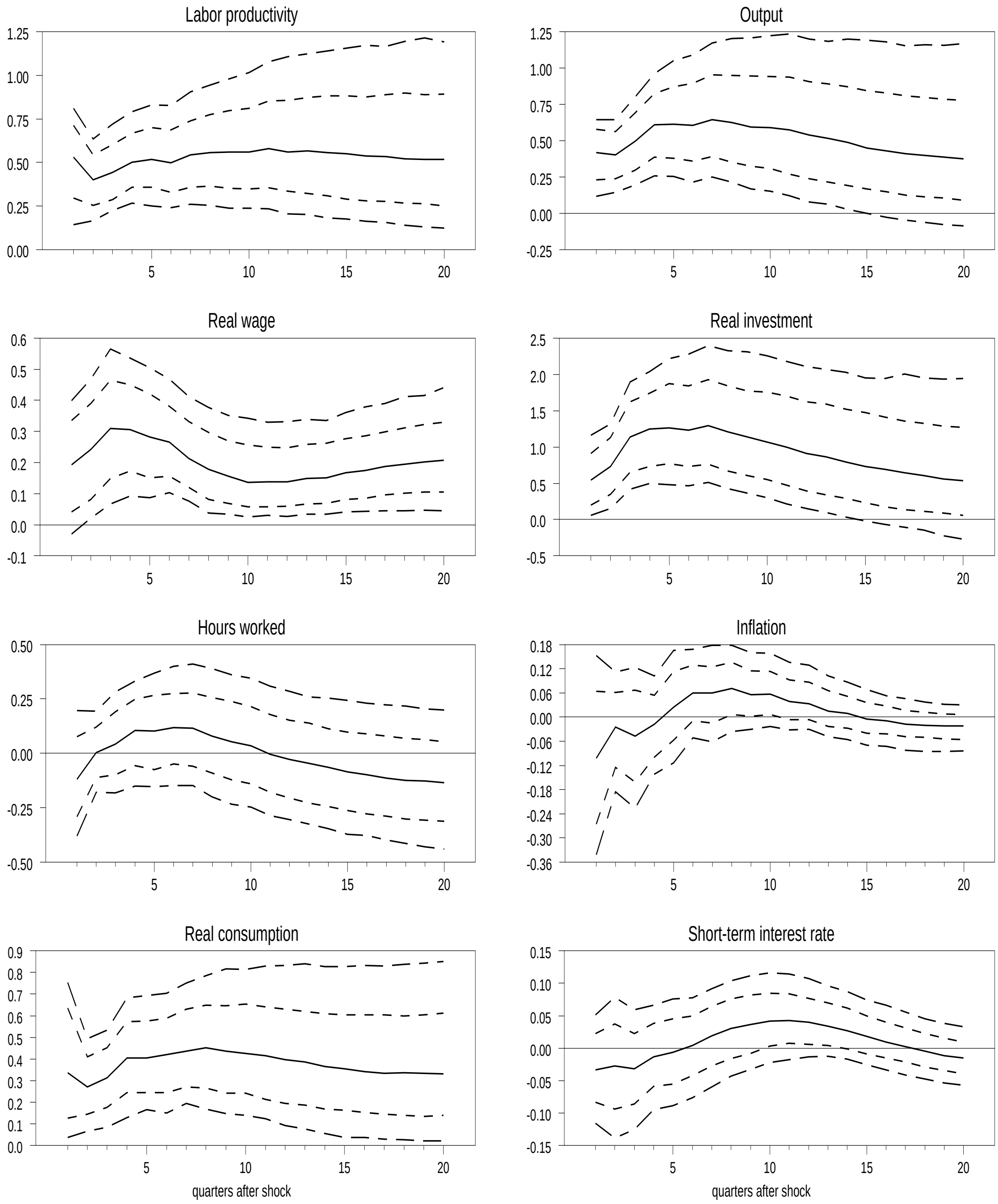


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a] All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 1983:1-2003:4.

Fig. 7A Impulse responses to positive technology shock: Japan

Benchmark specification[a]

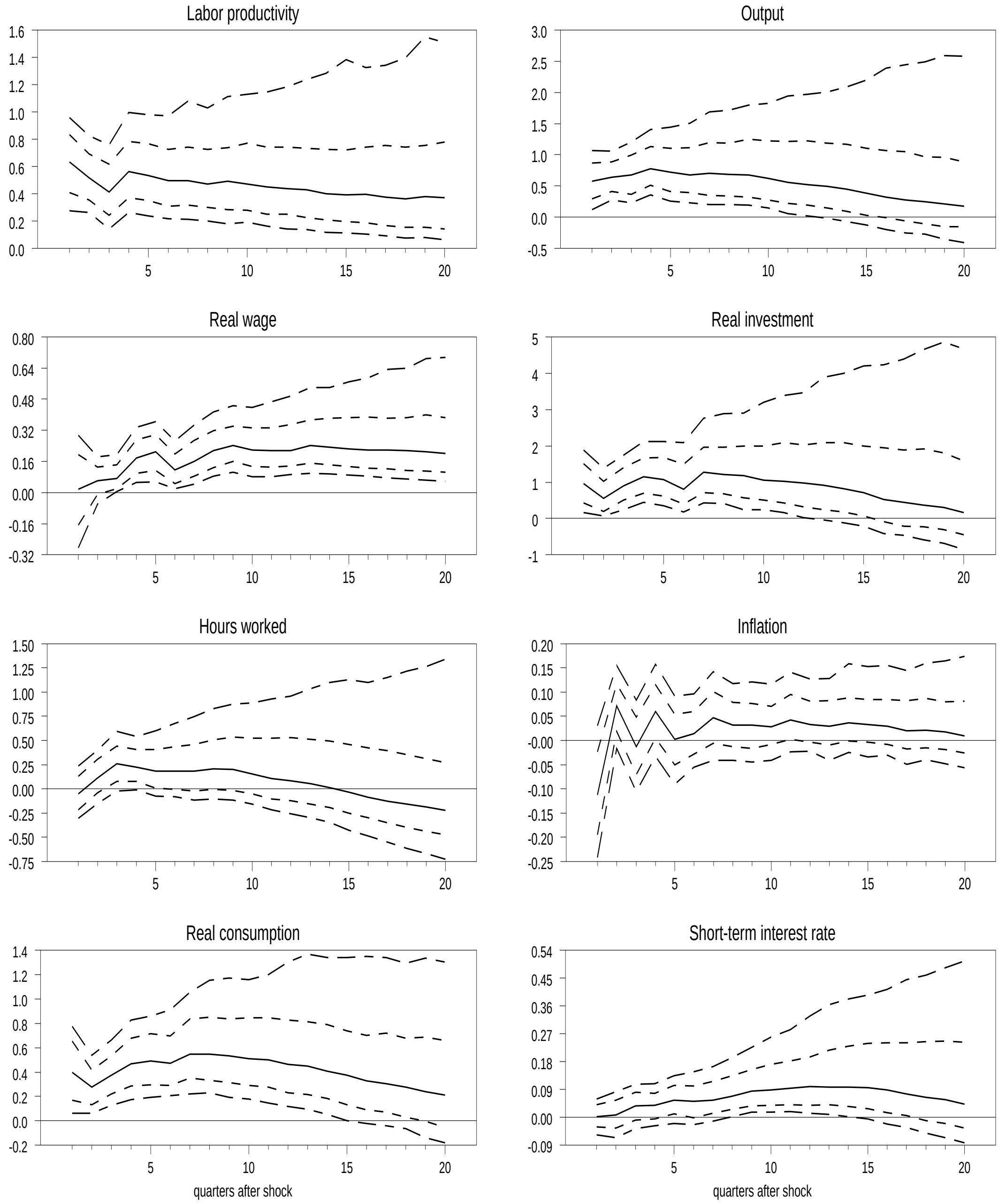


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a]All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 1970:2-2002:2.

Fig. 7B Impulse responses to positive technology shock: Germany

Benchmark specification[a]

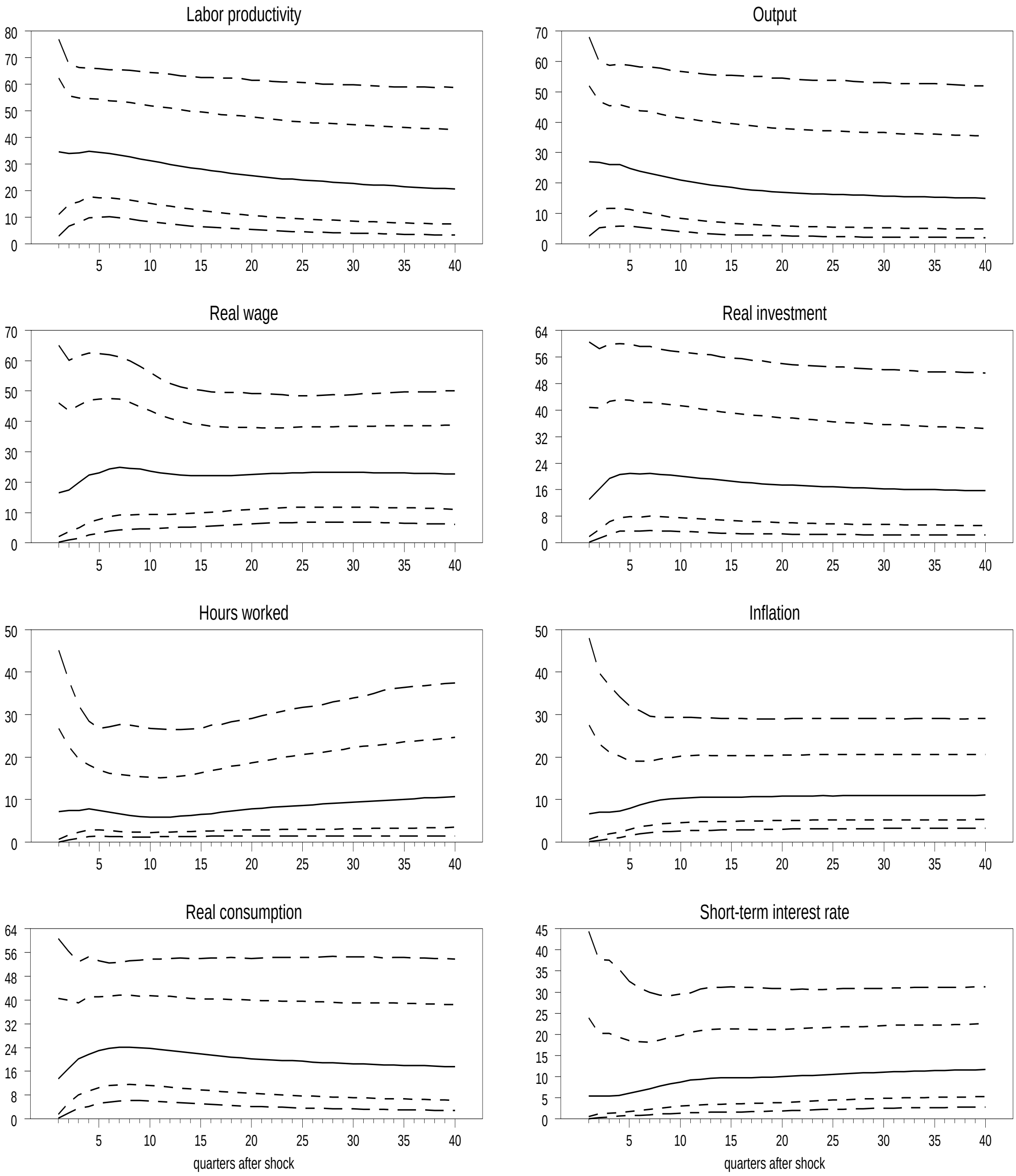


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a]All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 19761:1-1994:4.

Fig. 8A Contribution of technology shocks to forecast variance: Japan

Benchmark specification[a]

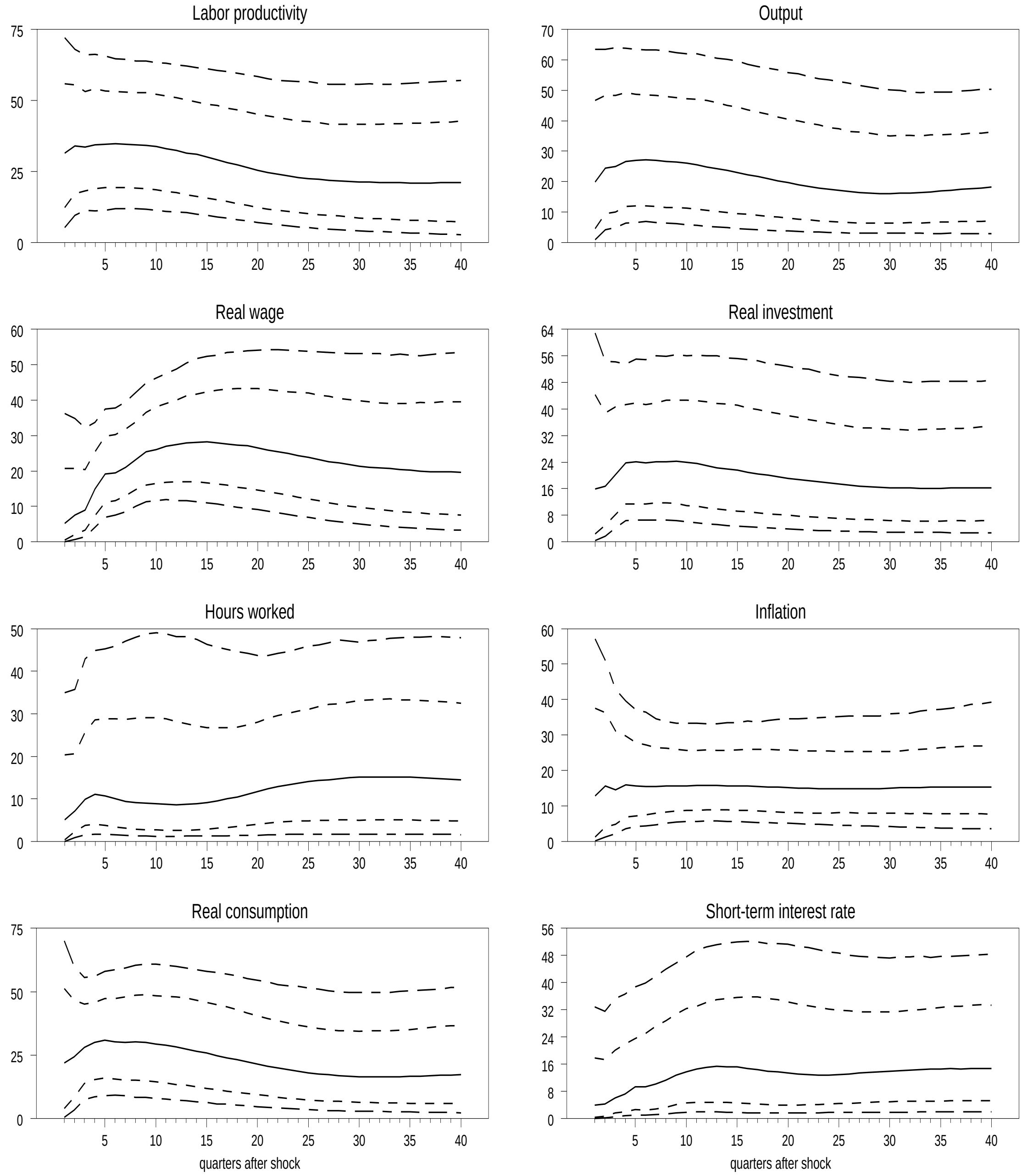


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a]All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 1970:2-2002:2.

Fig. 8B Variance decomposition: Germany

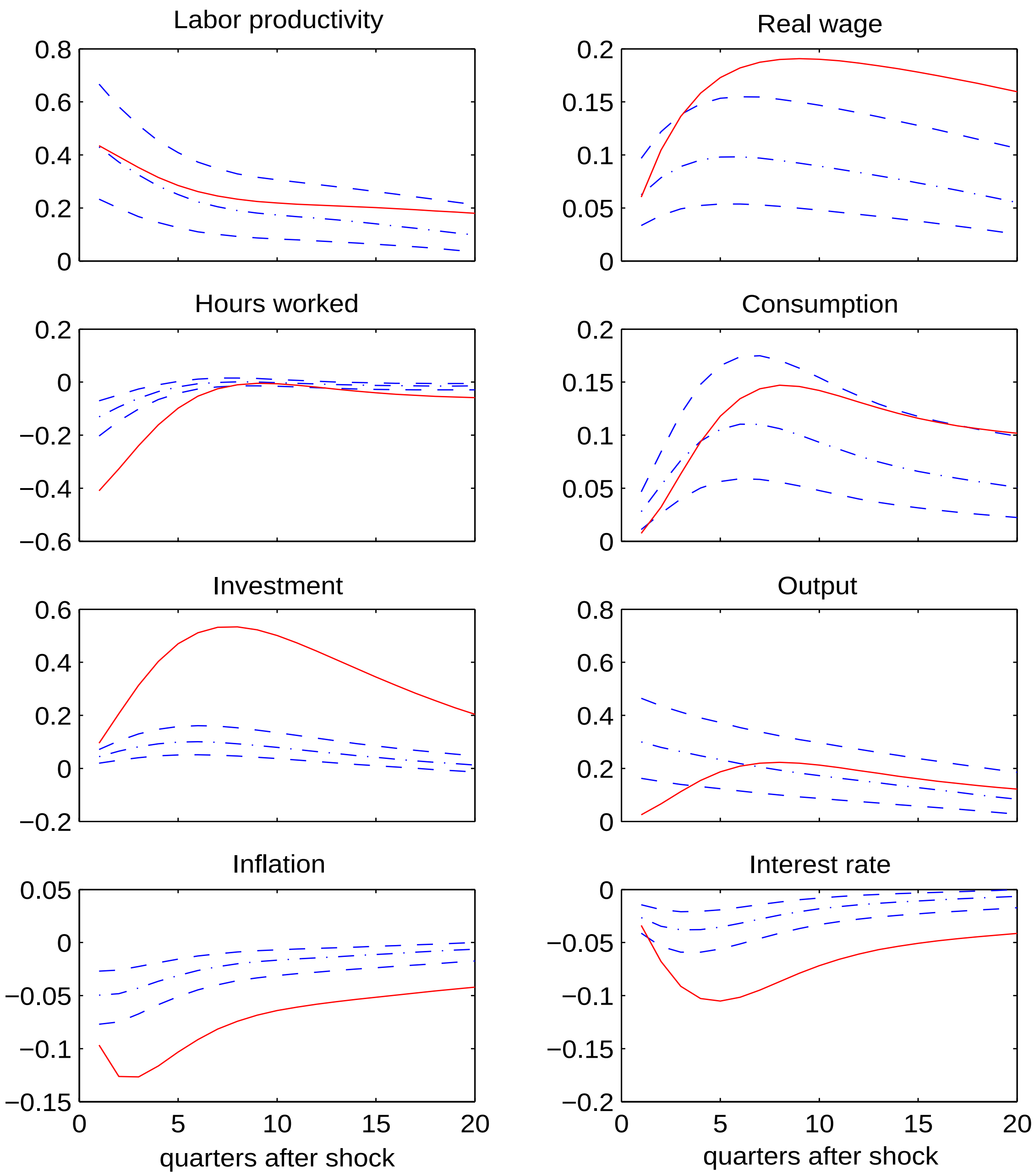
Benchmark specification[a]



— median   – – 16, 84 percentiles   — – — 5, 95 percentiles

[a]All variables in levels. Assumed sign restrictions are reported in Table 2. Sample period is 19761:1-1994:4.

Fig. 9 Impulse responses to positive technology shock: Simulated data[a]

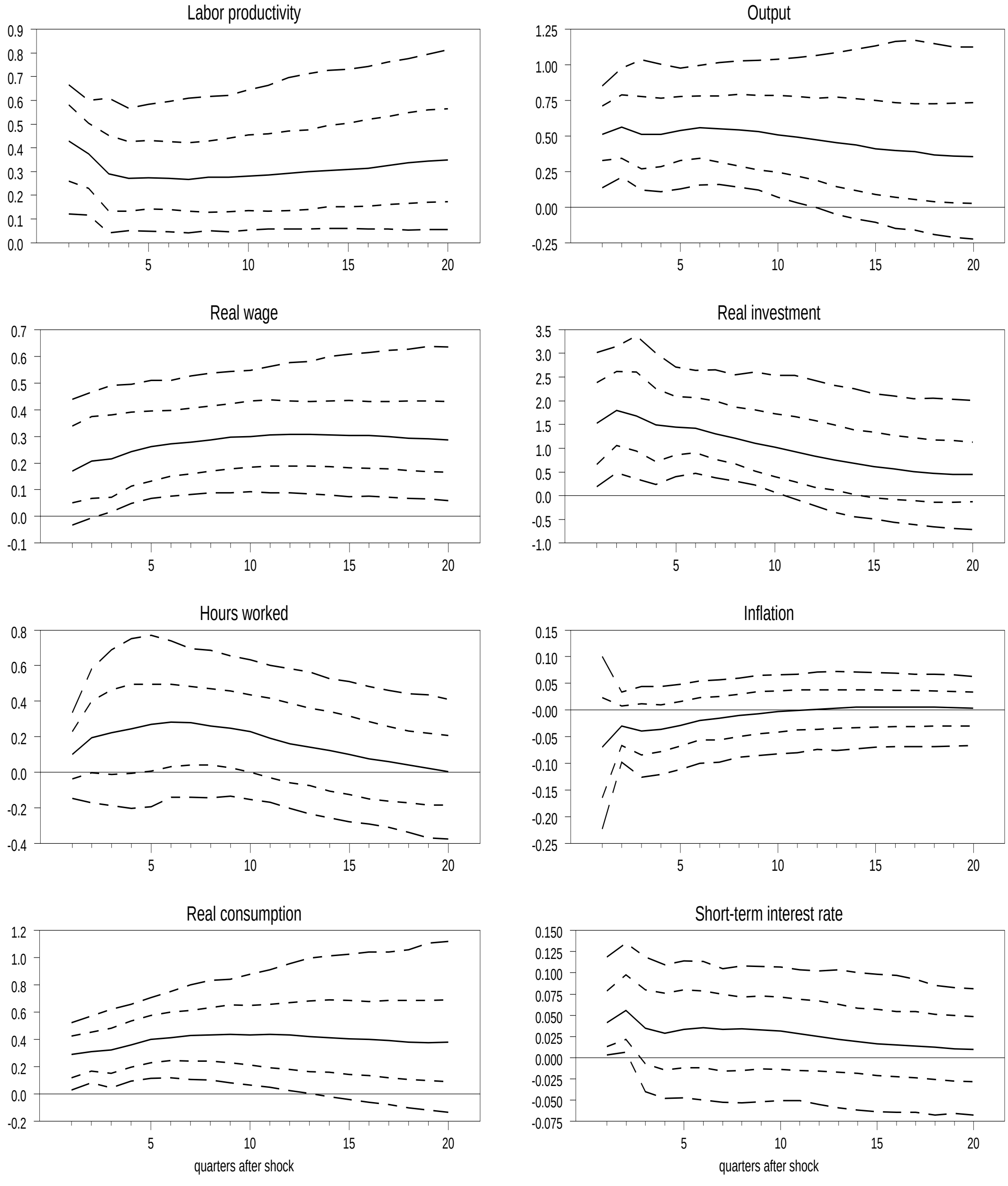


– · – median   – – 16, 84 percentiles

[a]Simulations carried out under parameterization in Table 3. The solid line reports the theoretical impulse responses.

Fig. 10 Impulse responses to positive technology shock: United States

The effect of assuming a positive interest-rate response[a]

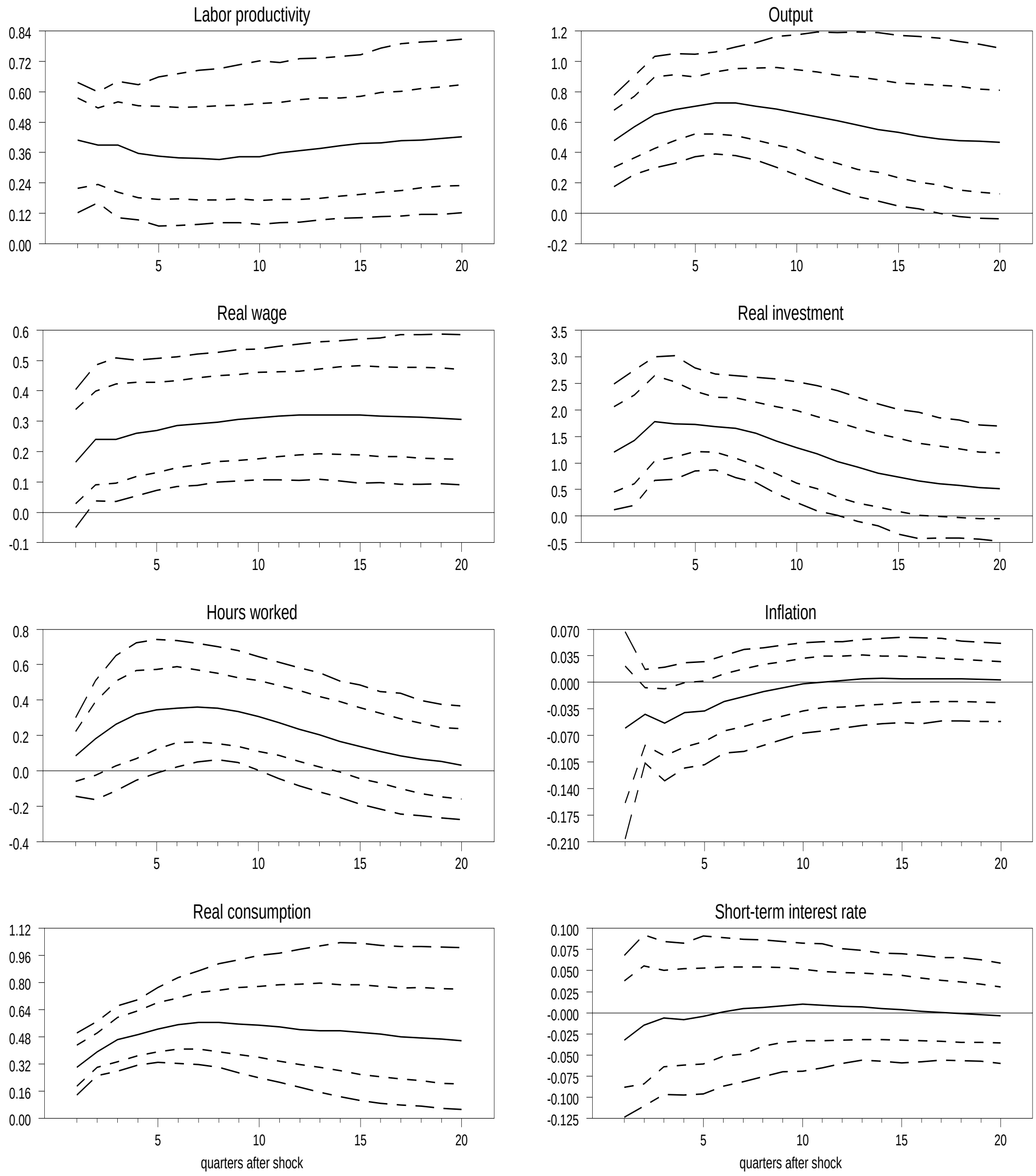


— median   – – 16, 84 percentiles   — – — 5, 95 percentiles

[a]All variables in levels. Sample period is 19531:1-2003:4. Assumed sign restrictions are reported in Table 2 with the additional requirement of a positive response of the Federal funds rate in the first 2 quarters.

Fig. 11 Impulse responses to positive technology shock: United States

The effect of assuming a large response of consumption[a]

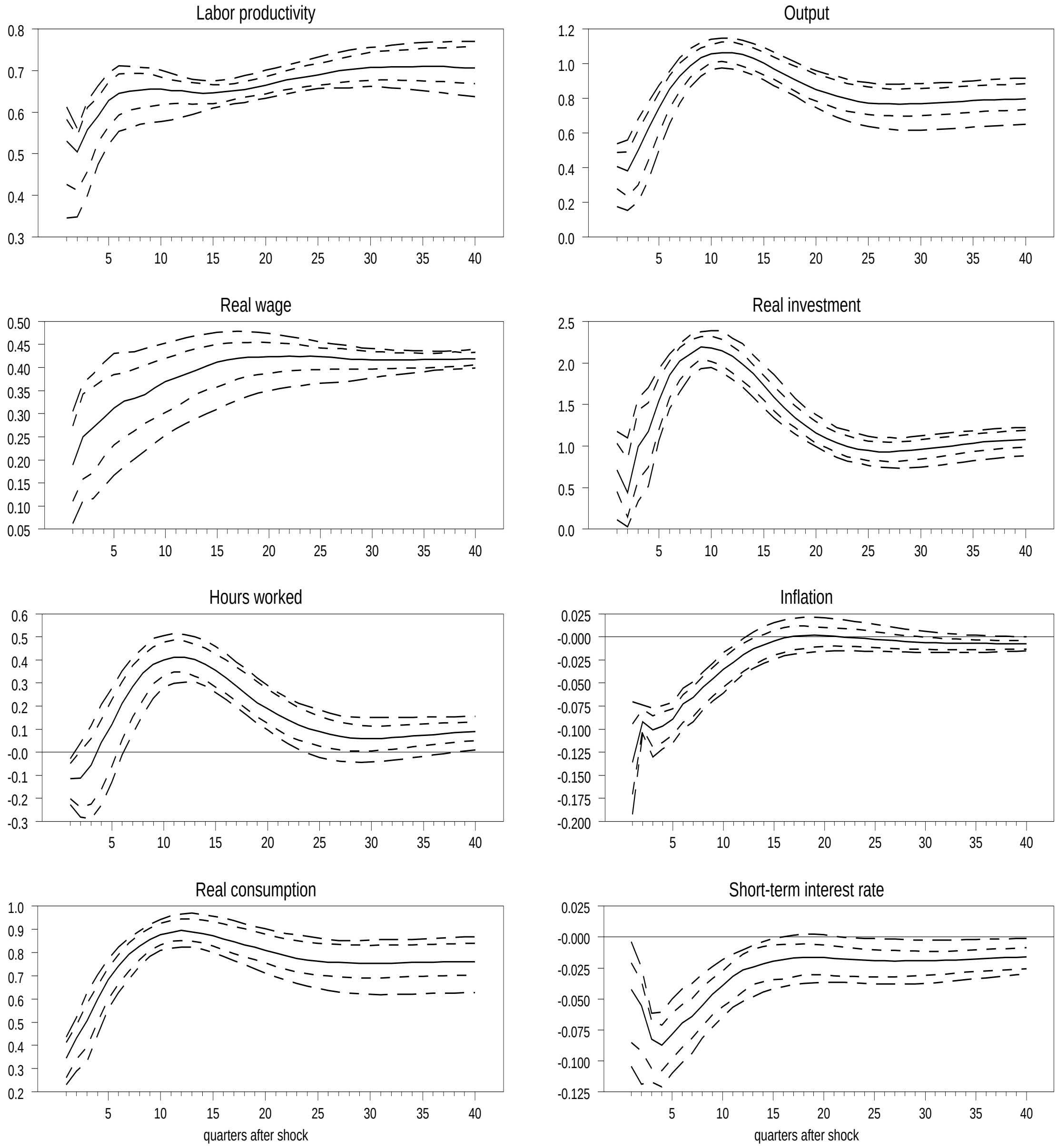


— median – – 16, 84 percentiles — – — 5, 95 percentiles

[a]All variables in levels. Sample period is 1953:1-2003:4. Assumed sign restrictions are reported in Table 2 with the additional requirement that for the first five quarters the response of real consumption is larger than the 16 percentile under the benchmark specification (see Figure 2).

Fig. 12 Impulse responses to positive technology shock: United States

The effect of requiring a large contribution to labor productivity long-run changes[a]



— median   – – 16, 84 percentiles   — – — 5, 95 percentiles

[a]All variables in levels. Sample period is 1953:1-2003:4. Assumed sign restrictions are reported in Table 2 with the additional requirement that technology shocks account for at least 70 percent of the variance of the forecast error of labor productivity at 40 quarters. The reduced form of the VAR and the covariance matrix of the residuals are fixed at their OLS-ML estimates.

Fig. A1 Data: United States

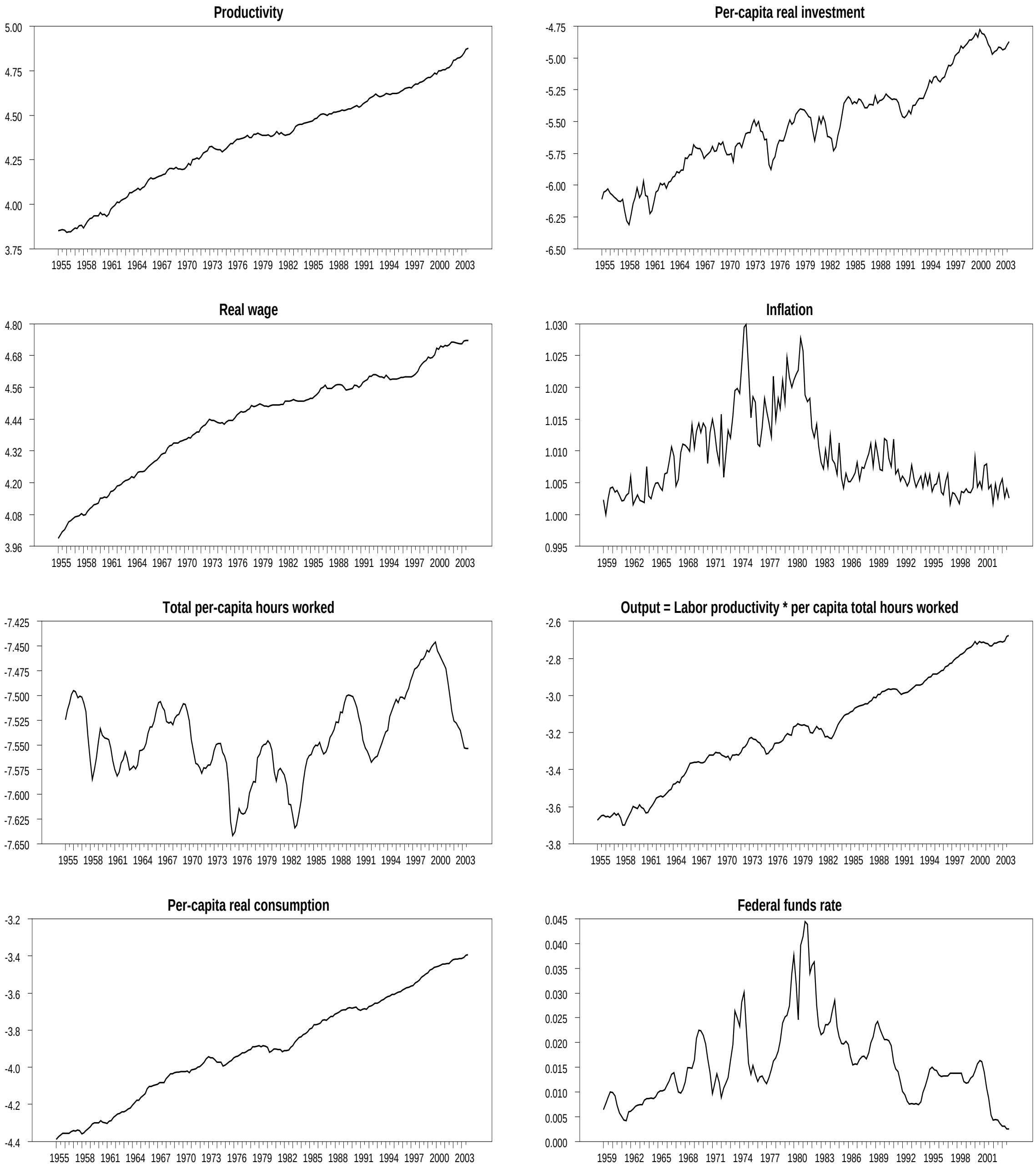


Fig. A2 Data: Japan

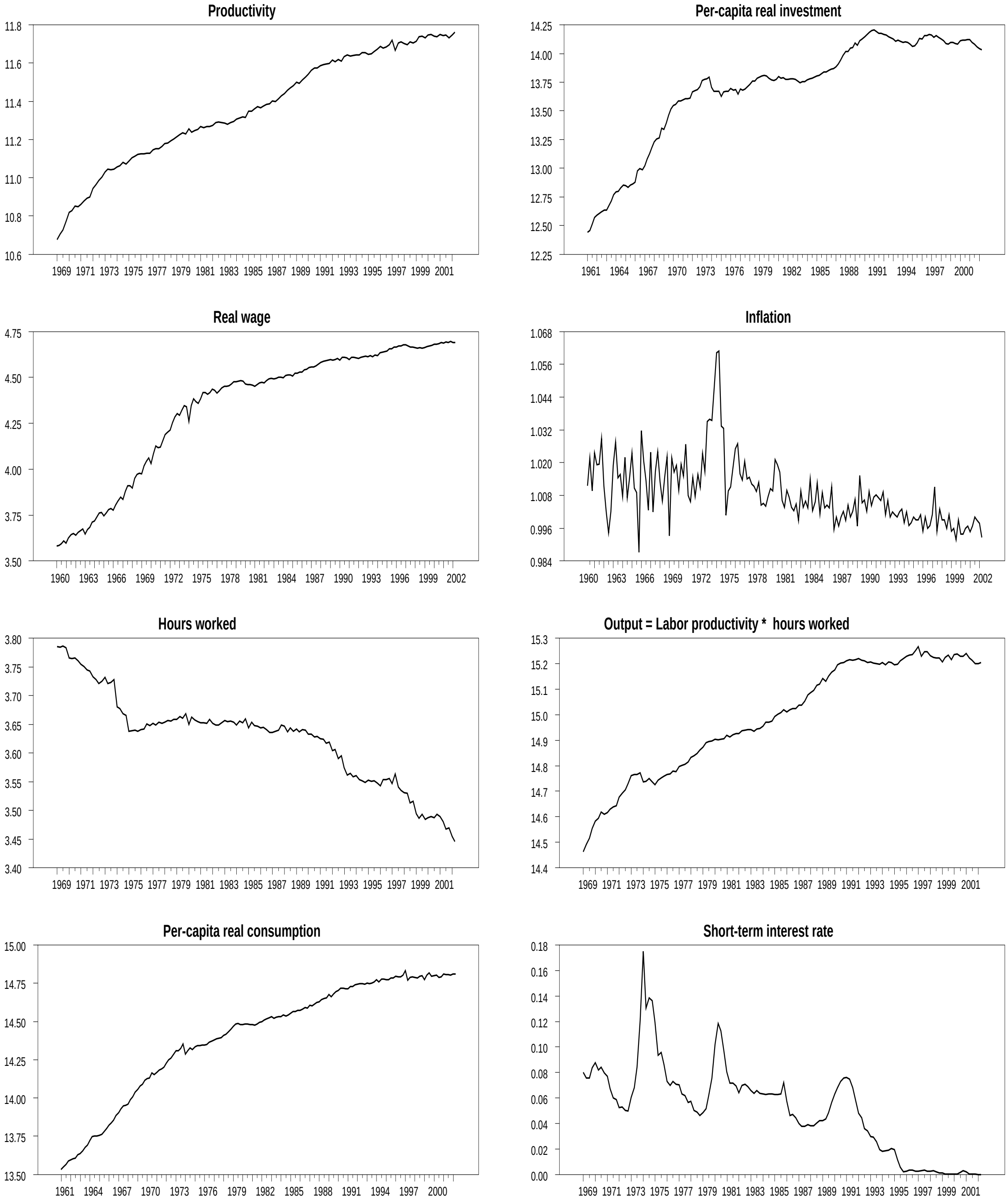


Fig. A3 Data: West Germany