Can the RBC hypothesis be rescued? A model-based VAR analysis*

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Abstract

This paper identifyies technology shocks in VAR models of the United States, Japan and West Germany by means of restrictions on the sign of impulse responses. These restrictions are derived from explicit priors on the parameters of a dynamic general equilibrium model encompassing both real and nominal rigidities. In all the countries technology shocks lead to a persistent increase in labor productivity, real wage, consumption, investment and output; hours worked increase with a humped-shape pattern. Only a limited subset of original parametrizations is consistent with these results.

JEL classification: C2, E3.

Keywords: Technology shocks; VAR models; Impulse responses; General Equilibrium Models.

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1 Introduction

The Real Business Cycle (RBC) research program has grown spectacularly over the last decade, as its concepts and methods have diffused into mainstream macroeconomics. As exemplified by the seminal work of Kydland and Prescott [1982], RBC theory assigns a central role to technology shocks as the source of the bulk of the aggregate fluctuations observed in the postwar U.S. economy. When persistent technology shocks are fed through a standard real business cycle model, the simulated economy appears to be able to match the patterns of unconditional second moments of key macroeconomic time series (e.g., see King and Rebelo [1999]).

However, RBC theory also yields strong predictions in terms of conditional second moments, namely, second moments conditional on a given source of fluctuations. A recent and influential literature, using structural VAR methods, argues that a key RBC conditional prediction, i.e., that a technology improvement should raise per capita hours worked, is at variance with the data. For instance, Galí [1999] and Francis and Ramey [2003], identifying innovations to technology as the only source of the unit root in labor productivity, find that hours worked fall after a positive technology shock. According to these estimates, the fall in hours is so persistent that technology shocks bring about a negative correlation between output and hours worked. Because hours worked are in fact strongly procyclical, Galí [1999] concludes that some other shock(s) must be driving aggregate fluctuations.

These results are important because they have promoted increasing skepticism that technology shocks are a major source of business cycles, attracting a great deal of attention.[1] On the one hand, there is a growing literature aimed at constructing models that can account for these findings.[2] On the other hand, some recent papers have challenged the very result that hours fall after a technology improvement, either using the same identification strategy to argue that it is not robust to changes in auxiliary assumptions on the number of and the time-series properties of the variables included in the VAR specification (e.g., Christiano, Eichenbaum and Vigfusson [2003]),

[1] Other recent papers, using very different methods, 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 [1999]).

[2] Galí [1999] has suggested nominal rigidities as the most natural explanation. Francis and Ramey [2003] argue that this finding is consistent with real business cycle models, modified to allow for richer sets of preferences and technology, such as habit formation and investment adjustment costs.

or radically questioning the "credibility" of the kind of atheoretical assumptions that are necessary to identify technology shocks with long-run restrictions (e.g., Cooley and Dwyer [1998]).

The goal of this paper is twofold. First, it identifies technology shocks with estrictions on the sign of impulse responses, similar to those proposed for monetary shocks by Canova [2001], Faust [1998] and Uhlig [1998]. These restrictions, however, are explicitly induced from priors on the parameters of a class of general-equilibrium models that are shown to be inconclusive about the response of hours worked to a technology shock. Second, it uses the information in estimated impulse responses to draw inference on the structural parameters of the theoretical models that are important in accounting for the dynamic effects of the identified technology shocks.

The identification strategy proposed in this paper substitutes weak theoretical restrictions for the atheoretical, auxiliary assumptions on the type of nonstationarity exhibited by the data, that are of crucial importance in the identification with long-run restrictions. As forcefully argued by Cooley and Dwyer [1998], the latter structural identification relies on the distinction between the almost observationally equivalent trend- and difference-stationarity of variables. We instead rely on weak economic restrictions on the responses of variables to technology.

These restrictions are weak for two reasons. First, they are derived from a wide range of parameterizations of a class of models encompassing both the RBC model with habits formation in consumption and investment adjustment costs of Francis and Ramey [2003], and the model with nominal rigidities and variable capacity utilization estimated by Christiano, Eichenbaum and Evans [2003] and Smets and Wouters [2002]. These restrictions, though requiring that the response of variables like labor productivity, real wages, consumption, investment and output be positive for several quarters, are rather uninformative concerning the response of hours worked, as labor inputs can either increase or fall after a positive shock to technology, regardless of the presence of nominal rigidities.

Second, sign restrictions are weak also in the sense that they do not lead to an exact identification of the reduced form VAR. Rather than as a shortcoming, we view this as an important advantage of this approach, since it eschiews "incredible" exact restrictions, e.g. exclusion restrictions, that are likely not to be robust to small perturbations to models specification. For instance, our sign restrictions are valid independently of the fact that technology shocks be exactly I(1). We build on the methodology in Canova [2001], characterizing the set of structural matrices whose associated impulse responses satisfy the theoretical sign restrictions. In estimating impulse responses, we take into account both data and identification uncertainty. We do this by simulation, drawing from the posterior distribution of the reduced form VAR covariance matrix and coefficients and from the set of structural matrices consistent with the assumed sign restrictions.

We apply this methodology to a 7-variable VAR in levels for the U.S., Japan and West Germany. We find that a shock to technology has quantitative consequences not dissimilar from those that an RBC student would anticipate. A positive technology shock drives hours worked up, not down, in all countries. In addition it leads to a persistent rise in labor productivity, real wages, output, consumption and investment. At the same time, our results are consistent with the view that technology shocks play a substantial role in accounting for business cycle fluctuations, although they leave unexplained most of the variation in hours worked.[3]

We then asses the information content of the estimated impulse responses in terms of structural parameters as follows. We compute the distribution of structural parameters whose implied impulse responses are consistent with features of those estimated with VARs. We find that only a limited subset of our original parameterization satisfy these restrictions. In particular, while both theoretical models, when parameters are restricted this way, tend to underpredict the response of hours worked to a technology shock, the RBC model has more difficulty than the nominal rigidities model in replicating other features of the estimated impulse responses. Moreover, when compared to estimation results of similar models in the literature, the above distribution of the structural parameters of the nominal rigidities model appear to attach a low probability to previously reported point estimates of several common parameters, in particular those that govern the internal propagation mechanism in the model.

What accounts for the differences in our findings about the behavior of hours relative to the literature discussed above? To answer this question we explore the dynamic implications of the technology shocks recovered by our procedure, focusing on two different kinds of structural matrices. The first kind implies that a positive shock brings about an increase in hours worked, the second kind implies that hours worked fall on impact. We find that, while the former set identifies technology shocks that have persistent but transitory effects, the latter are associated with

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

basically permanent effects of technology shocks on the other variables, especially labor productivity. Thus, these shocks have dynamic effects that are very similar to those identified by means of long-run restrictions.

Nevertheless, there are two important differences that account for our result that, across all identifications that are consistent with our sign restrictions, hours worked increase. First, these permanent shocks still lead to a substantial increase in hours, though with a few quarters delay. This is in line with the results in Christiano, Eichenbaum and Vigfusson [2003], who show that the findings in Francis and Ramey [2003] and Galí [1999] are turned around when per capita hours worked are treated as a trend stationary process rather than as a difference stationary process, as do the latter authors. Since we specify the VAR in levels, following Sims, Stock and Watson [1990] — so that we do not have to take a stand on the time-series properties of the data, on which our theory provides no guidance as they are not robust across our model parameterizations — we share a level specification of hours with Christiano, Eichenbaum and Vigfusson [2003].[4]

Second, across all the identification schemes satisfying our sign restrictions, those associated with permanent shocks account only for a minor, though important, fraction of all possible ones. Our findings are thus in line with the RBC tradition, in which technology shocks are usually assumed to be very persistent but trend stationary. Conversely, technology shocks can be identified with long-run restrictions only if they are assumed to be difference stationary, thus inducing a stochastic trend in labor productivity. The problem is that the near observational equivalence of trend and difference stationary specifications is of crucial importance in this literature, because the structural identification relies on the distinction.[5]

[4] 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 suffer from weak instruments problems and therefore 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.

[5] As argued by Faust and Leeper [1994], long-run restrictions lead to results that are heavily dependent on auxiliary assumptions on the time series specification on, and number of the variables included in the VAR. While these assumptions about the type of nonstationarity exhibited by the data are testable in principle, unfortunately most such tests in practice lack power, and there is a large literature that argues that trying to make such distinctions

We show that following a different route, in which theoretical restrictions are substituted for atheoretical ones, can be more fruitful to robustly identify "credible" structural shocks in VARs.

The remainder of the paper is organized as follows. Section 2 briefly outlines the benchmark models, and reports the theoretical impulse responses of a selected vector of variables to different shocks that are used to identify technology shocks. Section 3 discusses our identification strategy and presents the results of the VAR analysis in terms of impulse responses and variance decomposition. In Section 4 some inference on the structural parameters of our theoretical economies is conducted. Section 5 offers concluding remarks.

2 The model economy

In this section we describe the model that is used as a laboratory to analyze the response of a selection of variables to technology shocks. The model is basically the one estimated by Christiano, Eichenbaum and Evans [2001] for the U.S. and Smets and Wouters [2002] 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 $(\hat{})$ denotes deviations of per capita variables from their baseline long-run growth path. We will then consider impulse responses in two versions of the model, the first one without nominal frictions — that can be thought as a generalization of the standard RBC model (e.g., Hansen [1985]) to encompass real frictions emphasized in the literature (see King and Rebelo [1999]) — the second one including nominal frictions and a reaction function for monetary policy. 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, letting them speak for themselves on this issue.

is a fruitless exercise given the typical length of aggregate time series.

2.1 Real frictions

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 estimated over the 1955:1-2001:4 period. This implies a 1.6% annual growth rate in per capita output, investment and consumption.

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. 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 following structural shocks: a technology shock ϵ^z, a capital tax rate shock ϵ^{τ_k}, a labor supply shocks ϵ^l, and an investment specific shock ϵ^i. As is customary in the literature, all these shocks are assumed to have an autoregressive representation of order one with a coefficient $\rho_j \in [0.75, 0.999]$, $j = z, i, l, , \tau_k$. This parameterization does not formally encompass the case of an economy with unit root shocks; 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 $\rho_j's$. 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.

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 $h \in [0.001, 0.8]$ measures the degree of habit formation, and the parameter $\sigma_c \in [1.00, 10]$ 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 $\sigma_c = 1$. $\hat{R}_t$ 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 (Tobin's q), $\hat{\imath}_t$ is the level of investment, $\chi \in [0.01, 5.0]$ is the inverse of the elasticity of investment to the price of capital goods, and ϵ^i_t is an investment-specific technology shock (see Fisher [2002]). 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).[6]

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

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

where $\hat{r}_t$ ($\overline{r}$) is (the steady state value of) the rental price of capital (determined solely by β and δ), $\hat{\tau}_{k,t}$ ($\overline{\tau}_k = 0.38$) is (the corresponding value for) the capital tax rate and $\delta \in [0.01, 0.05]$ is the depreciation rate. Because of variable capacity utilization, the following approximate 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], who set to 100.

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

The aggregate resource constraint and the capital accumulation equation close the RBC economy:[7]

$$\frac{\alpha\delta}{\overline{r}}\widehat{i}_t + \left(1 - \frac{\alpha\delta}{\overline{r}}\right)\widehat{c}_t = \alpha\widehat{k}_t + (1-\alpha)\,\hat{l}_t + \alpha\psi\hat{r}_t + \hat{\epsilon}_t^z, \tag{5}$$

$$\widehat{k}_{t+1} = \delta\widehat{i}_t + (1-\delta)\,\widehat{k}_t. \tag{6}$$

The variable $\hat{\epsilon}_t^z$ represents a technology shock shifting the production possibility frontier, while $\alpha \in [0.2, 0.5]$ 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

In the version with nominal rigidities, 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 [2002], the log-linearization of the first order condition for this problem delivers the following real wage equation, where the random variable ϵ_t^l represents a shock to the labor supply schedule:

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

The parameter $\xi_w \in [0.01, 0.8]$ 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

[7] As we abstract from movements in government expenditure, we are effectively assuming that changes in tax revenues are rebated lump-sum to agents.

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%.

The inflation equation 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 [2002]):

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

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 $\xi_p \in [0.01, 0.8]$ 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 0.9, but argue that this value is way to high given the evidence on individual price changes in Bils and Klenow [2002].

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 $\rho_r \in [0.0, 0.99], \rho_y \in [-0.2, 0.2], \rho_\pi \in [1.1, 2.0]$, encompassing most values estimated in the literature. Since several parameterizations of the above rule in the nominal economy transpire into local indeterminacy of the steady state, when we compute impulse responses we do not restrict ourselves to the case in which the steady state is locally unique, but report results also for the indeterminate case, selecting the lowest stable eigenvectors and setting to zero possible sunspots.

2.3 Translating priors on parameters into sign-restrictions on impulse responses

In this section we present and discuss the impulse responses of the model's variables to productivity and capital tax rate shocks.[8] The reason for considering the latter shock is that it has been argued that it may have effects that are similar to technology shocks.[9] The focus on the sign of impulse responses has two advantages relative to alternative approaches. First, the emphasis on sign restrictions does not require the imposition of a set of identifying assumptions that may not to be robust across different parameterizations of the model. Second, it does not require a full specification of the stochastic structure and long-run properties of the model that is an essential part of structural VARs with long-run restrictions. Indeed, both our theoretical and empirical impulse responses can be interpreted as deviations from a weakly specified long-run baseline that encompasses trend and difference stationarity.

In order to formally derive restrictions on impulse responses, we find it useful to specify a prior on the structural parameters of the model. 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 assume that all structural parameters are uniformly distributed over sufficiently wide ranges. Table 1 summarizes the ranges of the uniform distributions for the parameters of the model with nominal rigidities. As argued above, these ranges cover reasonable values for the parameters, encompassing most cases in the literature. Obviously, the priors for the RBC model can be thought 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

[8] We report impulse responses only for these shocks because both models have implications that allow us to disentangle labor supply shocks (akin to labor tax rate shocks) and preference shocks from technology shocks. To save on space we do not report these impulse responses, that are available upon request.

[9] In this version of the paper we do not consider investment specific technology shocks. First, in the RBC model their impulse responses can be disentangled from those to technology shocks, as they bring about negative comovements between investment and consumption in the first few quarters. Second, although the above is not true in the nominal rigidities model, once in the estimates we control for changes in capital tax rates shocks — that in the nominal rigidities model can be confused with investment specific shocks, the latter shock can be viewed as a particular form of technology shocks with delayed effects.

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 the specification of the particular form of the priors on the structural parameters of the model economy. In this sense our own priors 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 these restrictions in a VAR context than the whole shape of the implied distribution of impulse responses.

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 uniform distributions reported in Table 1 for the RBC model and the model with nominal rigidities (NR). For each draw we saved the responses to a one per cent positive technology shock and to a negative capital tax rate shock) and computed the 2.5 and 98.5 percentiles of their distributions. This ensures that parameters combinations that bring about too extreme responses are ruled out. This is particularly important in our setup with nominal rigidities, because we do not restrict our attention to the case in which the policy rule is such that the equilibrium is determinate.

The resulting responses are reported in Figures 1A to 1D. From Figures 1A and 1B it is clear that technology shocks have qualitatively similar effects on real variables in both models, irrespective of nominal rigidities. The clear-cut prediction is that, in response to a 1 percent positive technology shock, labor productivity, output, investment and consumption increase for several quarters. However, these positive responses can be more or less persistent, and become non positive more or less quickly, reflecting our rather uninformative priors on both the parameters governing the internal propagation mechanism and the serial correlation of the shock. Conversely, in both models hours worked can either fall or rise depending on the parameterization, not only on impact but up to 20 quarters after the shock. Moreover, their median response is negative for most quarters. Finally, Figure 1B shows that, for the parameters range considered, the sign response of inflation and the policy rate in the nominal rigidities model is a priori indeterminate as well.

In Figures 1C and 1D we report the impulse responses to a 10 percent reduction in the capital tax rate in both models. Figure 1C shows that in the RBC model this shock has different implications relative to the technology shock. In particular, it leads to negative comovements between output an labor productivity in the first couple of quarters, notwithstanding the fact that the model features variable capacity utilization, so that both variables could in principle increase when hours increase. Conversely, Figure 1D shows that the same does not occur in the model with nominal rigidities, so that there is no unique set of restrictions that would allow us to disentangle these two shocks in the data. Therefore, 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 controlled for it when estimating our reduced form VAR, before imposing the restrictions derived from the model with nominal rigidities. Since our results are unaffected, to save on space we do not report them in the paper.[10]

Given this results, the following two sets of restrictions on the signs of the impulse responses are imposed in the VAR analysis carried out in the following section. We dub the first the "RBC prior", according to which a positive technology shock increases labor productivity, real wages, investment and output for the first 10 quarters, and consumption for the first 6 quarters. According to the second prior, derived from the nominal rigidities model("NR prior"), a positive technology shock increases labor productivity for the first 10 quarters, investment and output for the first 5 quarters, real wages for 8 quarters from the 3rd to the 10th, and consumption for 4 quarters from the 2nd to the 5th. Both priors leave the response of hours, inflation and the interest rate unrestricted. Thus, the "NR prior" also represents an important robustness check on the "RBC prior". Notice also that we could have pushed some restrictions to quarters further out in time, but decided to be conservative along this dimension as well.

3 The VAR analysis

In this section we present our specification of the VARs and the results of the identification of the technology shocks by means of restrictions on the signs of impulse responses. The spirit of our exercise can be described as follows. The vector of the impulse responses of n variables up to k steps to a structural technology shock, given the reduced form 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 appropriate to assume a multivariate uniform prior over the support given by an hypersphere in

[10]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 Erceg, Guerrireri and Gust [2003] as tax shocks. This correlation is not significantly different from zero.

R^{nk} centered in 0. The specification of a model with a prior on structural parameters allows us to attribute all the probability mass to the event that the responses of m variables (e.g., labor productivity or output) be positive for s quarters, although all positive values are deemed equally probable.

In turn, to the extent that these restrictions do not lead to over-identifycation, they impose no constraint on the reduced form of the VAR, so that we can use standard methods for conducting inference on it. In the rest of this section, we begin by specifying the variables that enter in the VAR and the number of lags. We then proceed in computing impulse responses and variance decompositions to technology shocks using our sign restrictions.

3.1 Identifying technology shocks by means of sign restrictions

The variables that we include in the VAR are the level of log of labor productivity, the log of real wage, the log of per capita hours worked, the log of per capita real investment, the log of per capita real consumption, the quarterly inflation rate (based on the GDP deflator) and the short-term interest rate (see Sims, Stock and Watson [1990] on using variables in levels).[11] The sample periods are as follows: 1959:1 - 2002:3 for the U.S., 1970:2 - 2002:2 for Japan and 1976:1 1994:4 for West Germany. All the data were already seasonally adjusted. Figures A1-A3 in Appendix A.2 report the variables used in the estimation of the VAR model for the three countries. The selected number of lags is set such that the residuals of all the equations of the VAR are serially uncorrelated. The results of the Ljung-Box-Q test based over the first 10 autocorrelations for the residuals of the three VARs led us to choose 3 lags for the U.S. and West Germany, and 4 lags for Japan, respectively.

We now proceed to briefly describe our strategy to identify technology shocks by means of sign restrictions, following Canova and De Nicoló [2002]. As described in Appendix A.1, the estimated covariance matrix of the reduced-form VAR residuals, Σ, can be decomposed as follows:

$$\Sigma = PD^{\frac{1}{2}}Q_{m,n}(\nu)\,Q'_{m,n}(\nu)\,D^{\frac{1}{2}}P' \tag{10}$$

where D is the diagonal matrix of the eigenvalues and P the matrix of the corresponding eigenvectors of Σ. The matrices $Q_{m,n}(\nu)$, where $\nu \in \left[0, \frac{\pi}{2}\right]$, are orthonormal, namely they are such that

[11] For a more detailed description of the data see the Appendix.

$QQ' = I$, where I is the identity matrix.[12] With a 7-variable VAR there are 21 such matrices for each ν. The candidate matrix $PD^{\frac{1}{2}}Q_{m,n}(\nu)$ is then used to orthogonalize the VAR reduced form innovations and compute the impulse response function. If the latter is consistent with our sign restrictions, the above matrix assumes the structural interpretation of identifying technology shocks. Effectively, we characterize by simulation the set of all possible structural matrices $PD^{\frac{1}{2}}Q_{m,n}(\nu)$ consistent with the restrictions on the signs of the impulse responses by drawing from a uniform distribution over the overall set of matrices $Q_{m,n}(\nu)$, storing those that satisfy the restrictions. In computing confidence intervals for impulse responses, we combine identification and estimation uncertainty by applying our algorithm to draws from the posterior distribution of the estimated covariance matrix Σ. [13]

The estimated impulse responses to a positive technology shock under the RBC restrictions for the United States, Japan and West Germany are presented in Figures 2A to 2C, respectively. Those obtained with the restrictions implicit in the nominal rigidities model are presented in Figures 3A to 3C. These figures report the median and the 90 percent confidence intervals of the variables responses up to 20 quarters.

Figures 2A-2C show that in all the three countries a positive technology shock determines a very persistent increase in labor productivity and the real wage. The responses of these variables are significant for more than 10 quarters, beyond the horizon over which the restrictions are imposed; however, the shock appears to have permanent effects only in Japan. In all countries, the maximum response of real wages occur a few quarters after the impact. Investment and output basically increase for the assumed horizon, although more persistently in Japan, with the former responding between 2 and 4 times more than the latter. The response of consumption, less strong than that of output, is more persistent than the assumed 6 quarters in all countries, displaying a persistence pattern similar to that of labor productivity. Only in the U.S. its maximum response appears to be somehow delayed, occurring 3 quarters after impact.

With respect to the variables that are left unconstrained by our identification, only the response of hours is similar across all countries. The median response of hours worked is always positive and

[12] The indices m and n denotes the rows of the matrix that are rotated.

[13] A full description of the algorithm used to compute all the matrices and the confidence bands combining identification and estimation uncertainty is described in Appendix A.1.

increasing, reaches a peak between 2 and 5 quarters after impact, quickly reverting to zero. The response is significant at the 90 per cent level for 6 quarters in the U.S., for 2 quarters in Japan, never in Germany. This increase in hours is in contrast with the fall estimated in the literature using long-run restrictions to identify technology shocks, with the exception of Christiano, Eichenbaum and Vigfusson [2003].

Finally, the effect of technology shocks on inflation and the short-term nominal interest rate is different across countries. In the U.S. the price level falls for a few quarters an then increases, while interest rates rise persistently; neither response is statistically significant over the whole horizon, however. Conversely, in Germany and Japan both variables increase significantly; the hike in the German interest rate lasts up to three years.

Figures 3A-3C shows that the use of the less restrictive identification assumptions derived from the nominal rigidities model does not alter the main results above. The only appreciable difference between the two identification schemes is that in the U.S. the effects on all variables are now slightly less persistent. The median response of consumption and real wages remains positive on impact in all countries, although the latter is not significant in Germany. Hence, in the rest of the paper we will report results based on the first identification only, unless otherwise stated.

As mentioned above, in contrast to standard structural VAR analyses relying on just- or over-identifying restrictions to estimate a unique matrix that maps reduced form residuals into structural shocks, our procedure yields a number of identifying matrices. Therefore, we find it useful to characterize the set of matrices estimated with our procedure. First, though consistent with our identifying assumptions, it is clear from Figures 2A to 3C that these matrices potentially imply estimated impulse responses with very different quantitative and qualitative properties. Second, it is of some interest, in light of the different results in terms of the response of some variables that can be obtained, to compare them to those that are derived by means of alternative identification strategies, especially those obtained by means of long-run restrictions.

An immediate way to summarize our results is presented in Figures 4A-4C, reporting the distributions of the estimated impact responses to a technology shock across all orthonormal matrices satisfying the RBC restrictions. These distributions were computed by Monte Carlo simulations in the following way. Keeping the VAR reduced form covariance matrix Σ and coefficients fixed at their maximum likelihood estimates, we drew a large number of rotation matrices $Q_{m,n}(\nu)$ from their uniform distribution, storing the structural matrices whose impulse responses satisfy the sign restrictions. We then estimated the distribution of the impact response of each variable by means of the RATS instruction *density.* These estimated distributions are reported in Figures 4A-4C.

Consider for instance the third chart in the left column of Figure 4A, displaying the distribution of the impact response of U.S. per-capita hours worked. Two features of this distribution immediately stand out. First, it is much less dispersed than our prior, with most of the probability mass concentrated in a relatively small interval, even when compared to its theoretical counterparts in Figures 1A-1B. This feature, common across all distributions, will be shown to have substantial implications in restricting the range of the structural parameters that are consistent with this evidence.

Second, this distribution is multimodal, with probability mass concentrated around a 0.25 and -0.10 percent impact response. This striking characteristic is shared only by some U.S. and Japanese distributions in Figure 4A and 4B. In particular, the distribution of the impact response of hours in Japan is also multimodal, with probability mass concentrated around a positive and a negative value as well. Indeed, the correlation between the impact response of hours and that of labor productivity after 20 quarters, computed across all identifications, is -0.96 in the U.S. and -0.51 in Japan. This finding is potentially very important in light of the debate in the literature concerning the response of hours worked to technology shocks identified through long-run restrictions. For instance, the minimum (negative) value of the impact response of hours in our identification is -0.25 percent, not far from that estimated by Francis and Ramey [2003]. Thus, we decided to further explore this feature, looking at the pattern of impulse responses implied by the structural matrices associated with the maximum and minimum response of hours to our identified technology shocks.

Strikingly, we found that these matrices imply very different quantitative properties of the dynamic effects of technology shocks. These results are presented in Figures 5A to 5C, where the continuous line denotes the responses computed with the matrix associated with the maximum increase in hours, and the dashed line denotes the responses computed with the matrix associated with the fall in hours. From Figure 5A, reporting the responses of U.S. variables, we see that technology shocks identified with the former matrix have effects that, though somehow less persistent, are in line with the median of those reported in Figures 4A. In particular, labor productivity, output and investment strongly increase on impact and then revert to their baseline, while real wages and consumption react more slowly. The response of hours is positive and increasing in the first year following the shock, when it starts to decline, becoming negative in the third year. Inflation and the short-term interest rate both increase quite persistently.

Conversely, not only do technology shocks identified with the second matrix reduce hours worked for the first 4 quarters, but also have basically permanent effects on labor productivity, that after 5 years is still 0.5 percent higher than its baseline, pretty much the same magnitude of its impact response. Hours worked become positive only after one year from the shock and peak in the third year, but reach a maximum value close to that attained under the alternative identification; afterwards they decline more slowly. The responses of real wages, output, consumption and, to a less extent, investment, are positive from impact and very persistent, all displaying a hump-shaped pattern similar to that of hours. With the exception of investment, all these variables respond more to the permanent technology shock. Moreover, this same shock bring about a persistent fall in inflation and nominal interest rates.

Therefore, it seems that in the data two patterns of technology shocks coexist, with effects of similar magnitude on impact but with different dynamics and persistence. The first shock, initially bringing about an increase in hours worked, has temporary effects; the second one, initially bringing about a fall in hours worked, appears to have permanent effects on most variables. It is thus likely the latter should be predominant in the identification with long-run restrictions, accounting for the common finding of countercyclical labor inputs in this literature. Interestingly, the different response of hours may be rationalized in both our baseline models with the larger, in absolute value, negative wealth effect stemming from the permanent shock.[14]

This same pattern is not present in Figures 5B and 5C, reporting responses in Japan and West Germany, respectively. In Japan, the two structural matrices recover a quite similar permanent response of labor productivity, that is however associated with different responses not only in hours worked, but also in consumption, investment, inflation, short-term interest rates and, obviously, output. The technology shocks associated with an impact increase in hours brings about a more pronounced increase in all these other variables as well. We see from Figure 5C that in Germany

[14]Notice that in order to reconcile the 0.5 percent increase in labor productivity and the 0.25 percent increase in hours on impact with a disturbance different from a techonology shock, e.g. a labor supply shock, would require capacity utilization $\widehat{u}_t$ to increase by almost 2 percent, assuming $\alpha = 1/3$.

both the maximum and minimum (only slightly negative) impact response of hours are associated with two shocks that only slightly differ in terms of persistence and magnitude of their effects. In particular, the more subdued response of hours is brought about by the shock having the less persistent and smaller effects.

3.2 Technology shocks and aggregate fluctuations

What are the implications of our estimates in terms of the contribution of the technology shocks to aggregate fluctuations? We address this issue by computing the percent of the variance of the 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) however, accounting for the bulk of cyclical fluctuations in hours (and inflation and interest rates) would require considering other sources of disturbances. In this latter respect, our results are not very dissimilar from those obtained with long-run restrictions.

Figures 6A to 6C presents the variance decomposition results at horizons up to 40 quarters. The three lines in each chart were computed taking into account only the uncertainty on the identification. Namely, keeping the VAR reduced form covariance matrix Σ and coefficients fixed at their maximum likelihood estimates, we drew a large number of rotation matrices $Q_{m,n}(\nu)$ and stored those associated with impulse responses satisfying the sign restrictions. We then computed the 5th, 50th and 95th percentiles of the distribution of the response of each variable at each horizon. These values are reported as the dashed and continuous lines in Figures 6A to 6C. This way, we can directly ask whether technology shocks can explain a large fraction of variability in output, investment, consumption and so on, under any reasonable identification, where reasonable is taken to mean that they have to satisfy our theory-based sign restrictions.

We see from Figures 6A-6C that, across the different identification schemes, technology shocks can explain a substantial fraction of the variability in labor productivity, output and investment up to 12 quarters in all three countries. For longer horizons, this fraction falls below 50 percent in the U.S. for investment, labor productivity and, eventually, for output. In Japan and Germany, technology shocks can explain most of the variability in these variables up to all horizons considered. In the U.S. and Germany the fraction of the variance of real wages explained reaches a peak after 12 quarters, and remains around 50 percent up to 40 quarters. Technology shocks play substantial role in the variance of consumption in Japan, accounting for over 50 percent of the forecast error variance at all steps. These shocks also play an important, if smaller role in accounting for variation in consumption in the U.S. and Germany, and the real wage in Japan, never exceeding 40 percent on horizons beyond 16 quarters.

In all the countries, the explained fraction of variability in hours is always substantially below 50 percent, with a median of around 10-15 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 that the bulk of movements in hours should reflect shocks different from those affecting technology. Interestingly, in the RBC literature the fact that other shocks would be needed to account for features of labor markets, in particular comevements between hours and productivity, has been noticed since the early contributions of Kydland [1984] and Christiano and Eichenbaum [1992].

Finally, turning to nominal variables, Figures 6A to 6C indicate that technology shocks do not play an important role in the forecast error variance for inflation and the interest rate, with the sole exception of the latter in West Germany. In contrast, Christiano, Eichenbaum and Vigfusson [2003] find that technology shocks identified with long-run restrictions play a substantial role in inflation, accounting for over 60 percent of the one step ahead forecast error variance and almost 40 percent at even the 20 quarter horizon.

4 Fron estimated impulse response to structural parameters

So far we have focused on the implications of our estimates in terms of impulse responses and variance decomposition to technology shocks. However, we started out our exercise by motivating restrictions on impulse responses with an explicit prior on the structural parameters of our model economies. Thus, it is natural to ask whether we can go all the way and draw implications on the parameterizations that are more likely to be associated with the estimated dynamics of technology shocks. This exercise could address important questions, e.g., whether the fact that consequences of a technology shock resemble those in a real business cycle model might in reality reflect that the actual economy has various nominal frictions, and monetary policy has successfully mitigated those frictions.

In principle, if the mapping from parameters to impulse responses could be inverted, we should be able to map the distribution of impulse responses back into a distribution of structural parameters. However, there are two nontrivial aspects of this task. First, we suspect that in general it would be very difficult to show that such an inverse mapping exists under general conditions. Second, although we can generate as many impulse response vectors as we wish, they are in general high-dimensional object whose density is not easy to approximate. For instance, computing the distribution of impulse responses of our 8 variables up to 20 quarters would amount to the formidable task of non-parametrically approximating a density function from $R^{160} \rightarrow R^{+}$.

Therefore, to give a flavor of the potential benefits from this approach to parameters inference, as a first pass we focus on the much simpler problem of determining the parameters' distributions such that the implied impulse responses have the following properties: (i) their median must fall within the confidence bands reported in Figures 2A and 3A, and (ii) their 5th and 95th percentiles must be arbitrarily close to those reported in Figures 2A and 3A. Clearly, we are ignoring other important features of impulse responses, beyond the information incorporated in those percentiles. In practice, we computed these distributions by simulation, drawing from the parameters priors and computing impulse responses, storing the draws consistent with the above requirements. Our findings for the estimates of the RBC and nominal rigidities model with U.S. data are reported in Figures 7A-7B and 8A-8B, respectively.

Consider first Figures 7A and 7B. Figure 7A reports the 5th, 50th and 95th percentile of the impulse responses up to 10 quarters in the model and the data, the latter denoted with stars (*). Figure 7B reports the distribution of the parameters of the RBC model that is consistent with the impulse responses in Figure 7A. The latter were obtained imposing requirements (i) and (ii) for 8 quarters on labor productivity, real wage, hours, investment and consumption. Two results stand out. First, Figure 7A shows that the RBC model has a hard time in replicating all of the impulse responses at the same time. The median response of hours is negative on impact and in general quite far from its estimated counterpart. The median of the wage response falls outside the 90 percent data confidence interval on impact, and even its lower bound falls only marginally inside it. This is due to the tight link in the model between real wages and labor productivity, making it very difficult to match the empirical behavior reported in the figure.

Second, Figure 7B shows that in spite of its coarseness, the information summarized in the width of the confidence intervals of the estimated impulse responses is enough to greatly reduce the initial uncertainty on most structural parameters. The distribution of β, h, χ, σ_c, σ_l, ρ_z, and σ_z are now concentrated, displaying a clear unique mode. In particular, the evidence shifts most of the probability mass towards high values of the intertemporal elasticities of leisure and consumption (low values of σ_c and σ_l); a low value of investment adjustment costs χ and the capacity adjustment parameter ψ, and a high value of the habits parameter h, in order to account for the limited response of consumption; a high persistence of the shocks ρ_z and a small value of their standard deviation σ_z, the former in line with those calibrated in the RBC literature using TFP measures, the latter substantially smaller.

The results of the same exercise for the nominal rigidities model are reported in Figures 8A, 8B1 and 8B2, obtained imposing requirements (i) and (ii) above on the theoretical responses of labor productivity, hours, real wages, consumption, investment and inflation up to 8 quarters. Two results stand out. First, Figure 8A shows that the nominal rigidities model can replicate all impulse responses better than the RBC model. In particular, wage stickiness appear to be important in accounting for the different behavior of real wages and labor productivity in the data. However, in the model the responses of the nominal variables, inflation and especially the interest rate, tend to be more negative than in the data, revealing that in order to match the estimated dynamic effects of technology shocks systematic monetary policy has to accommodate the increase in output above its trend.

Second, as shown in Figure 8B1-8B2, despite the large number of parameters, all distributions are concentrated, displaying a clear unique mode, with the exception of that of σ_l, λ_w, α that do not look different from their original uniform priors. Similarly to what occurs with the RBC estimates, relative to the priors, the evidence shifts the probability mass towards high values of the intertemporal elasticities of consumption (low values of σ_c), a rather low value of investment adjustment costs χ, a rather low value of the capacity adjustment parameter ψ, a relatively high value of the habits parameter h, a high persistence of the technology shock ρ_z and a small value of its standard deviation σ_z. However, some inferential results on common parameters are consistent with a rejection of the RBC model. Interestingly, the densities of the adjustment probabilities ξ_w and ξ_p are concentrated away from zero and around similar values, as high as 0.6, also close to those estimated by Christiano, Eichenbaum and Evans [2003] using impulse responses to monetary shocks. The parameters γ_w and γ_p distributions are concentrated around values close to 1, implying a high degree of indexation to past inflation for both prices and wages. Finally, the parameters of the policy reaction function are quite precisely estimated, around values somehow different from those of the typical Taylor rule, but not far from those implied by optimal policy in similar settings. In particular, ρ_y turns out to be significantly lower than 0, while ρ_π significantly larger than 1.5.

5 Concluding remarks

[to be completed]

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Appendix A.1 The identification of technology shocks

This section describes the algorithm designed to identify the technology shocks. The reduced form VAR has the following representation:

$$X_t = c + B(L) X_{t-1} + U_t \tag{11}$$

where the vector X includes the variables in level and c is a constant. The covariance matrix of the vector of residuals U_t is denoted with Σ. The reduced form is estimated consistently using ordinary least squares (OLS).

In identifying the technology shocks we follow Canova and De Nicoló [2002]. The estimated covariance matrix of the VAR residuals, Σ, is decomposed into PDP' where D is the matrix of eigenvalues and P the matrix of eigenvectors. We also considered the Cholesky decomposition of the covariance matrix Σ.

The designed algorithm searches along all possible rotation matrices $Q_{m,n}$ and angles ν that satisfy the restrictions on the signs of the impulse responses[15]. The matrices $Q_{m,n}$ are orthonormal, that is they imply that $QQ' = I$ where I is the identity matrix. With 7 variable in the VAR there are 21 ($\frac{N(N-1)}{2}$) possible matrices Q. An example of such matrices is the following:

$$Q_{m,n} = \begin{bmatrix} cos(\nu) & -sin(\nu) & 0 & 0 & 0 & 0 & 0 \\ sin(\nu) & cos(\nu) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Using the fact that $QQ' = I$, the decomposition of Σ becomes:

$$\Sigma = PD^{\frac{1}{2}}QQ'D^{\frac{1}{2}}P' \tag{12}$$

where we have made use of the property of orthonormality of the matrices Q. The inverse of the matrix $PD^{\frac{1}{2}}Q$ is used to compute the impulse response function. These are obtained combining the moving average representation of the reduced form VAR:

[15] The indices m and n denotes the rows of the matrix that are rotated.

$$X_t = C(L)\, U_t \tag{13}$$

where the matrix polynomial $C(L)$ is given by:

$$C(L) = \sum_{i=0}^{\infty} C_i L^i$$

with the matrix $A_0 = \left(PD^{\frac{1}{2}}Q\right)^{-1}$. Combining these two elements we obtain the structural impulse response function:

$$X_t = C(L)\, A_0^{-1} V_t \tag{14}$$

where V_t are the structural shocks. The algorithm stores all the the matrices A_0 that satisfiy the restriction imposed on the sign of the impulse responses.

The error bands are constructed in the following way. A draw for the inverse of the reduced form covariance matrix Σ is drawn from an inverted-Wishart distribution. A draw for the coefficients of the VAR is obtained from a Normal distribution with mean equal to the estimated (OLS) coefficients and covariance matrix equal to $\hat{\Sigma} \otimes \left(X'X\right)$. Given a draw of Σ and the coefficients of the reduced form VAR we can compute the impulse response function using (11). For each run of the Monte Carlo simulation we draw a value for the angle ν from a uniform distribution over the $\left[0, \frac{\pi}{2}\right]$ interval and we select randomly the $Q_{m,n}$ matrix using a uniform distribution. We then save all the responses that satisfy the restrictions on the sign of the impulse responses.

Appendix A.2 Description of the data

United States

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

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

Real wage: nominal hourly compensation, non-farm business sector (BLS), deflated with the implicit GDP deflator (source BEA).

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).

Real wage: wage rates in non-agricultural economy (Bank for International Settlements, 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 International Labor Office) 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
α	0.20	0.50	0.35
b	0.985	0.995	0.99
δ	0.01	0.05	0.03
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	0.01	0.8	0.405
γ_p	0.0	1.0	0.5
ξ_w	0.01	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	-0.2	0.2	0.0
ρ_π	1.1	2.0	1.55
ρ_z	0.75	0.999	0.8495
ρ_l	0.75	0.999	0.8495
ρ_i	0.75	0.999	0.8495
ρ_{tk}	0.75	0.999	0.8495

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

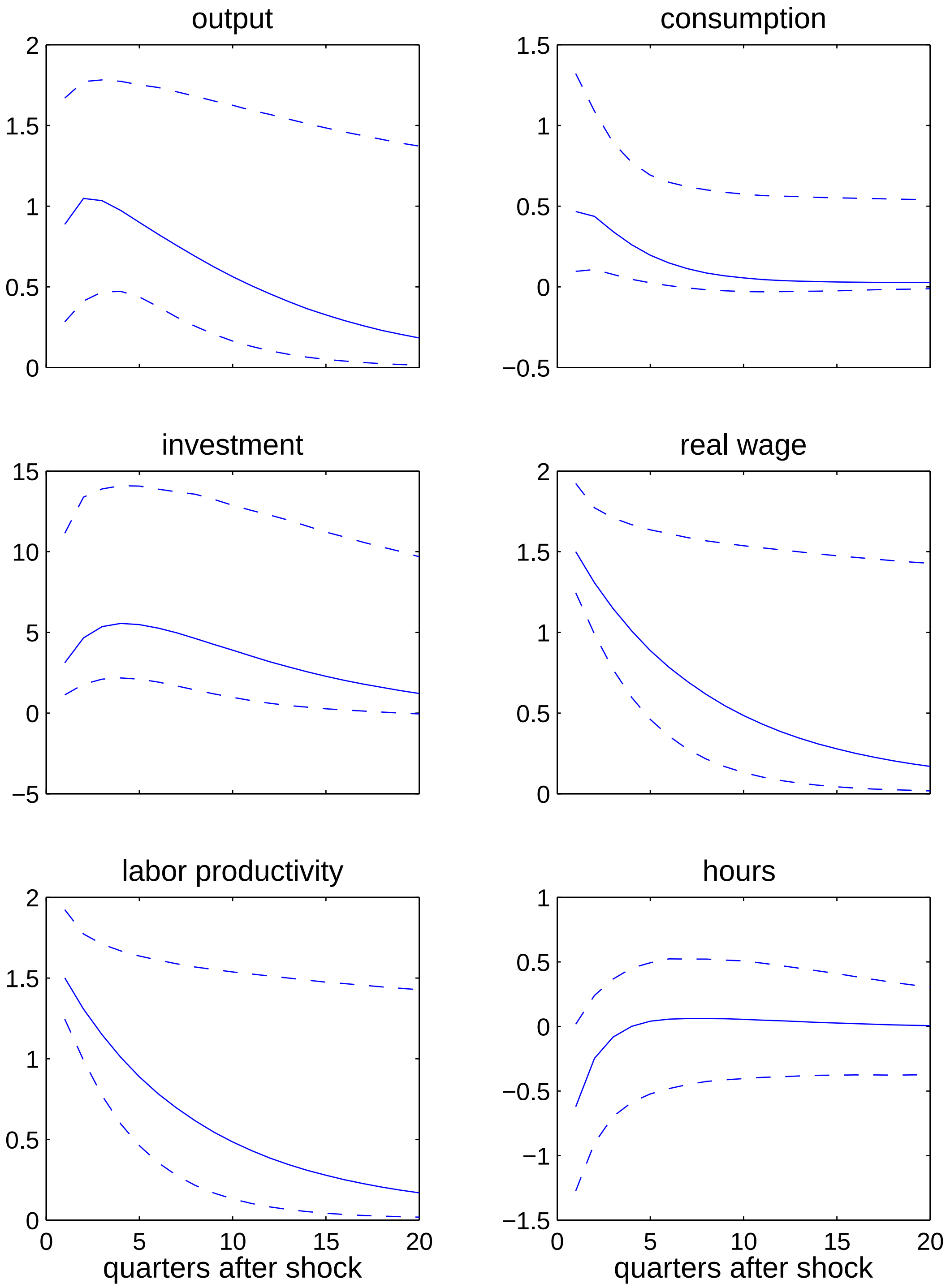

Fig. 1B Impulse responses to positive technology shock: NR model

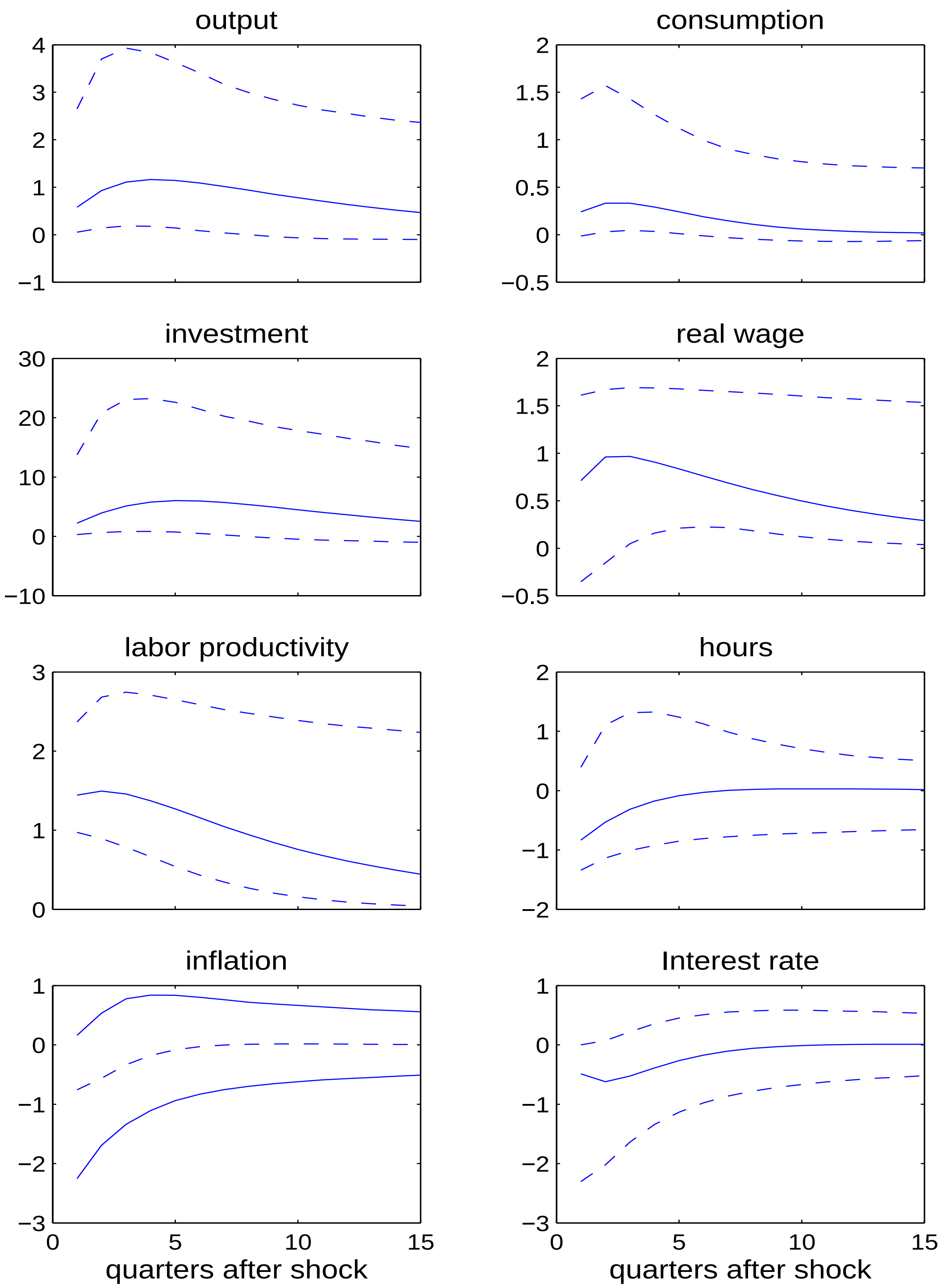

Fig. 1C Impulse responses to negative capital tax rate shock: RBC model

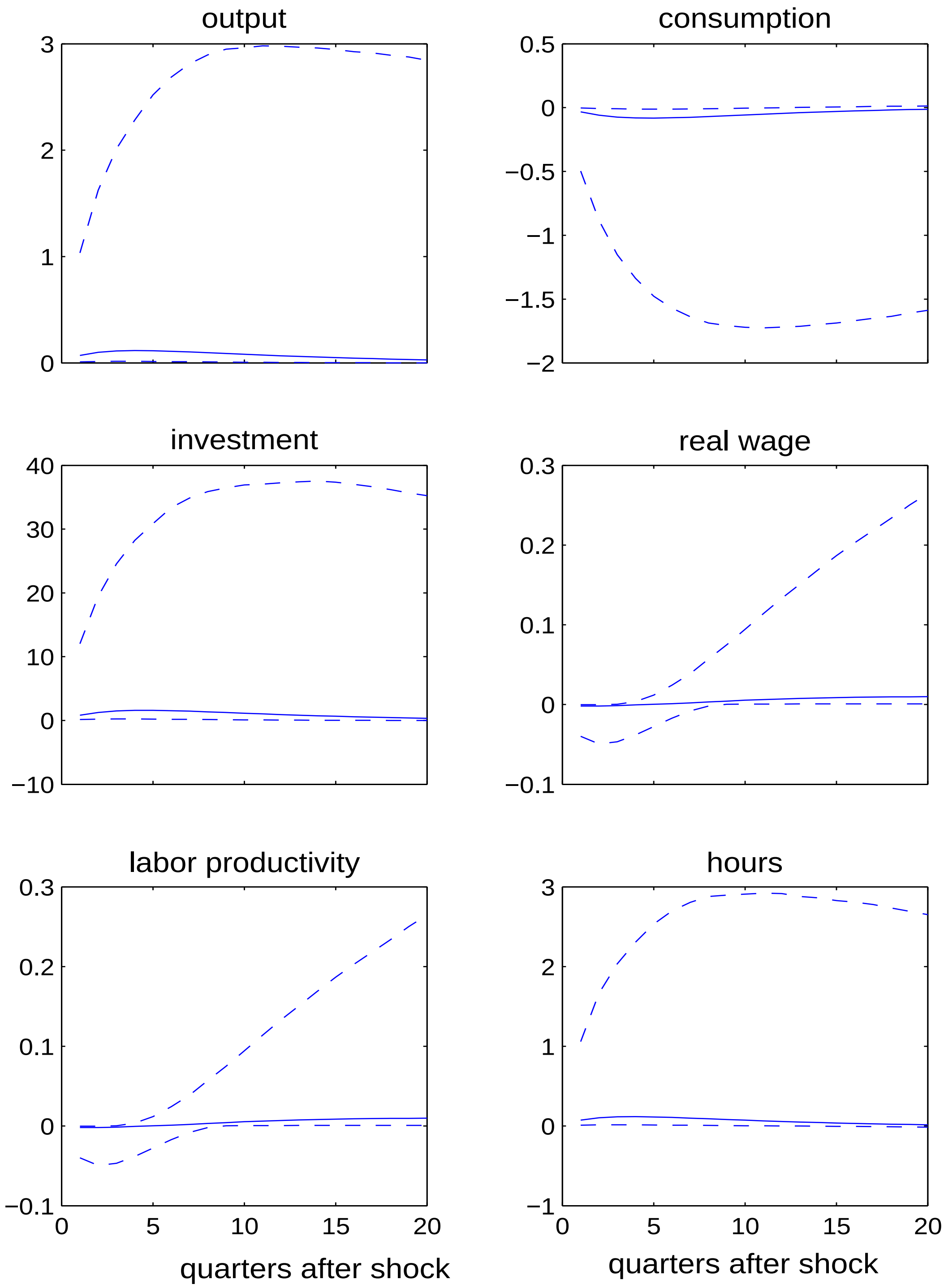

Fig. 1D Impulse responses to negative capital tax rate shock: NR model

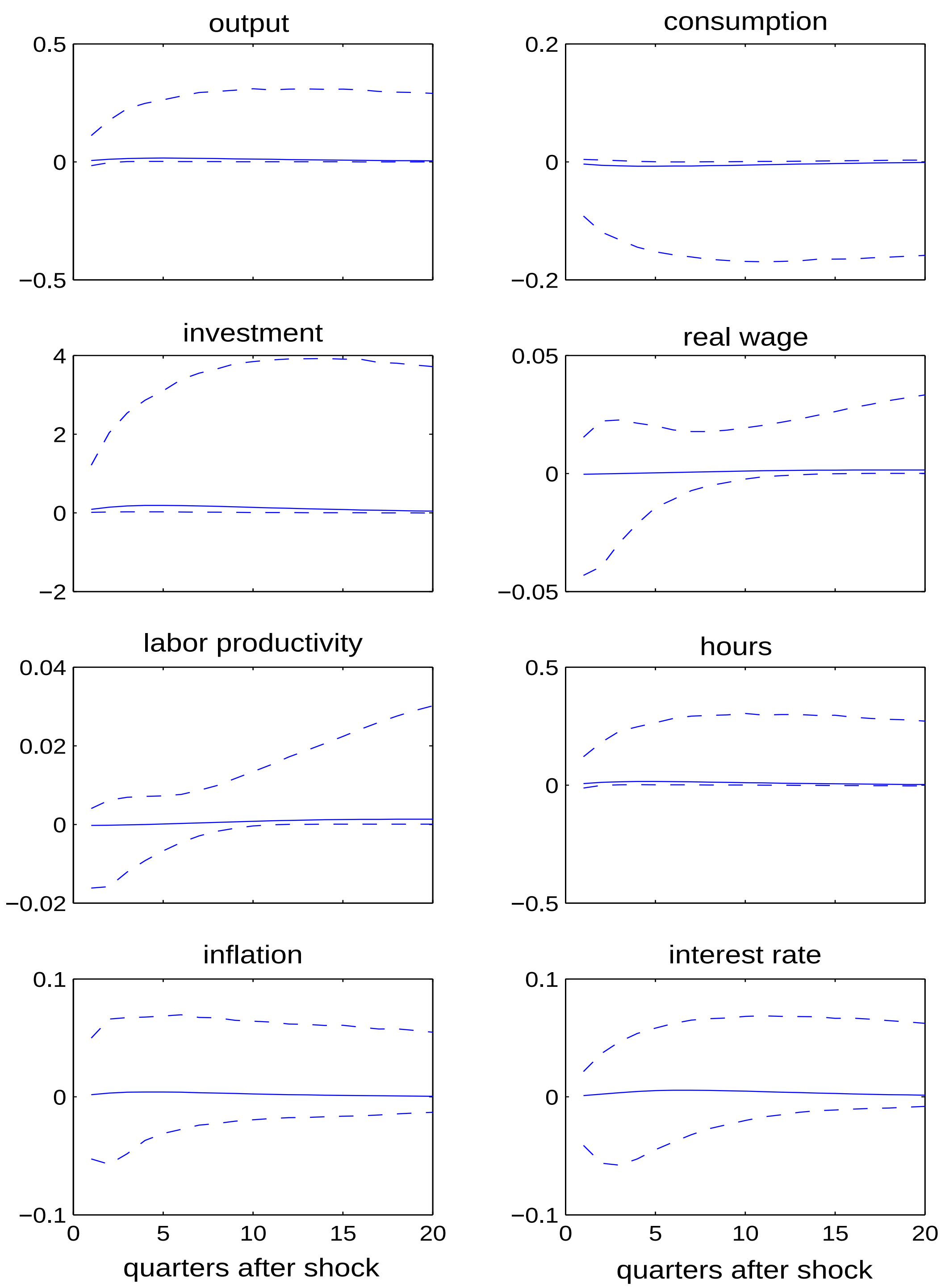

Fig. 2A Impulse responses to positive technology shock (RBC identification): United States

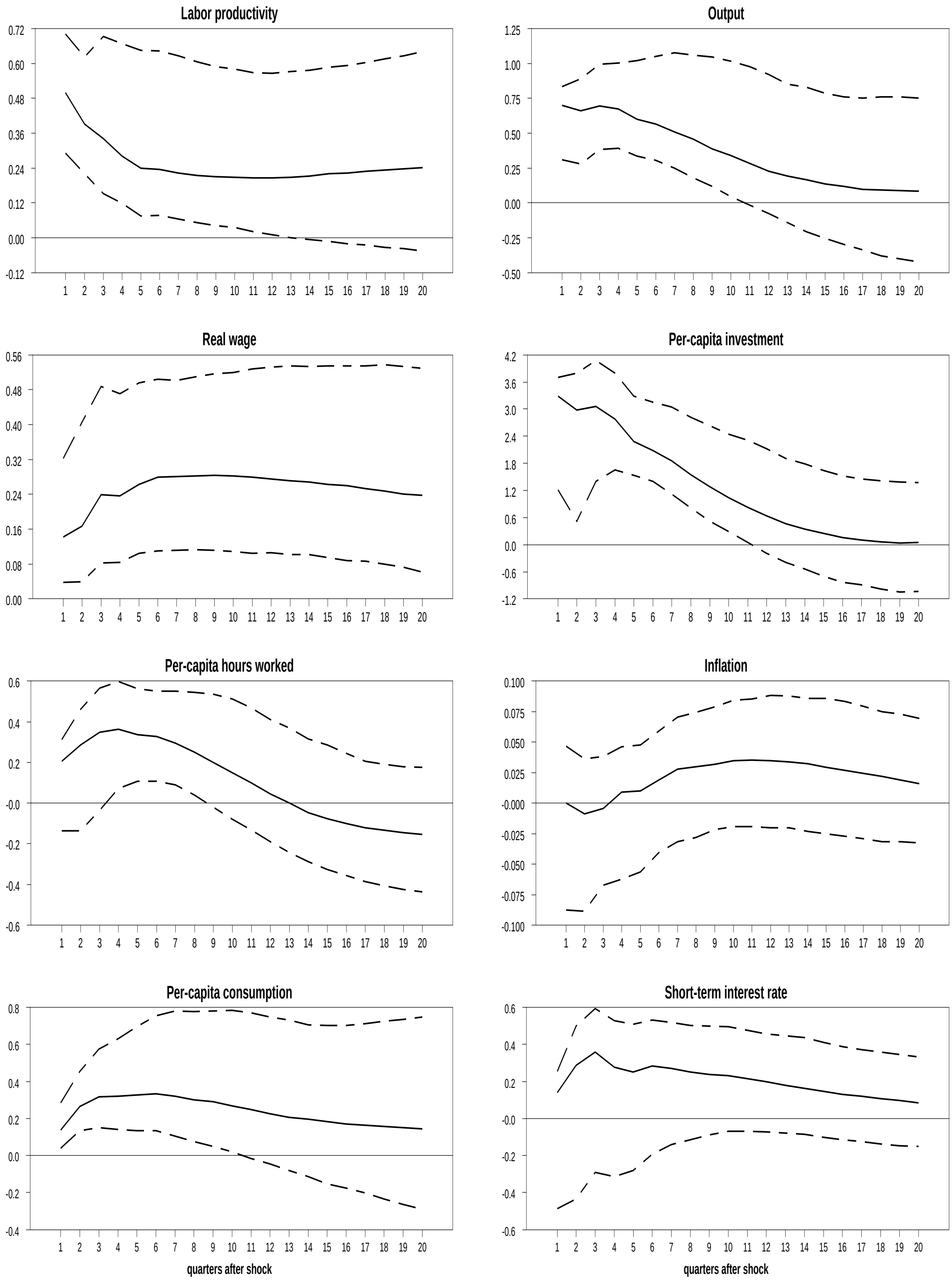

Fig. 2B Impulse responses to positive technology shock (RBC identification): Japan

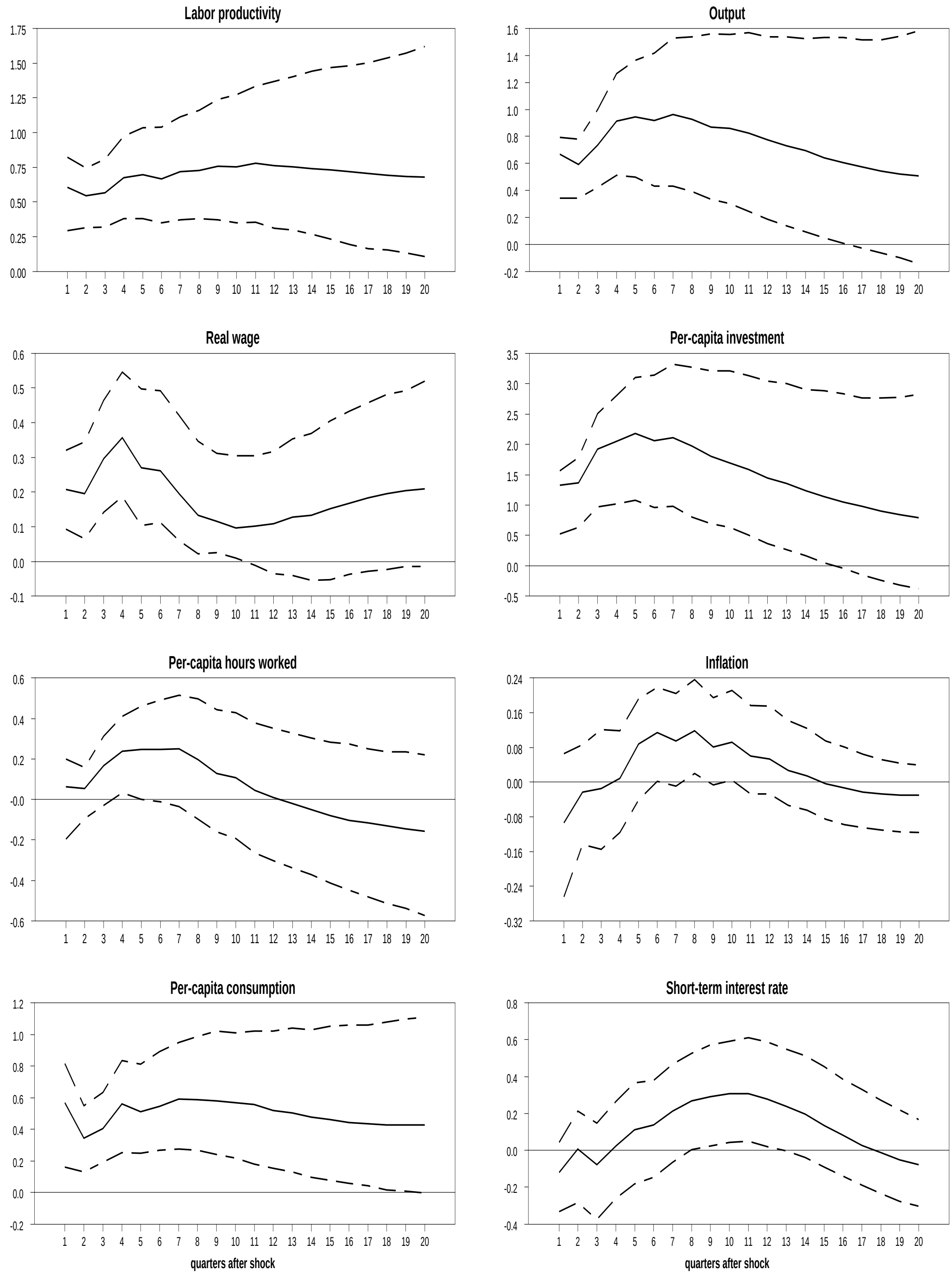

Fig. 2C Impulse responses to positive technology shock (RBC identification): West Germany

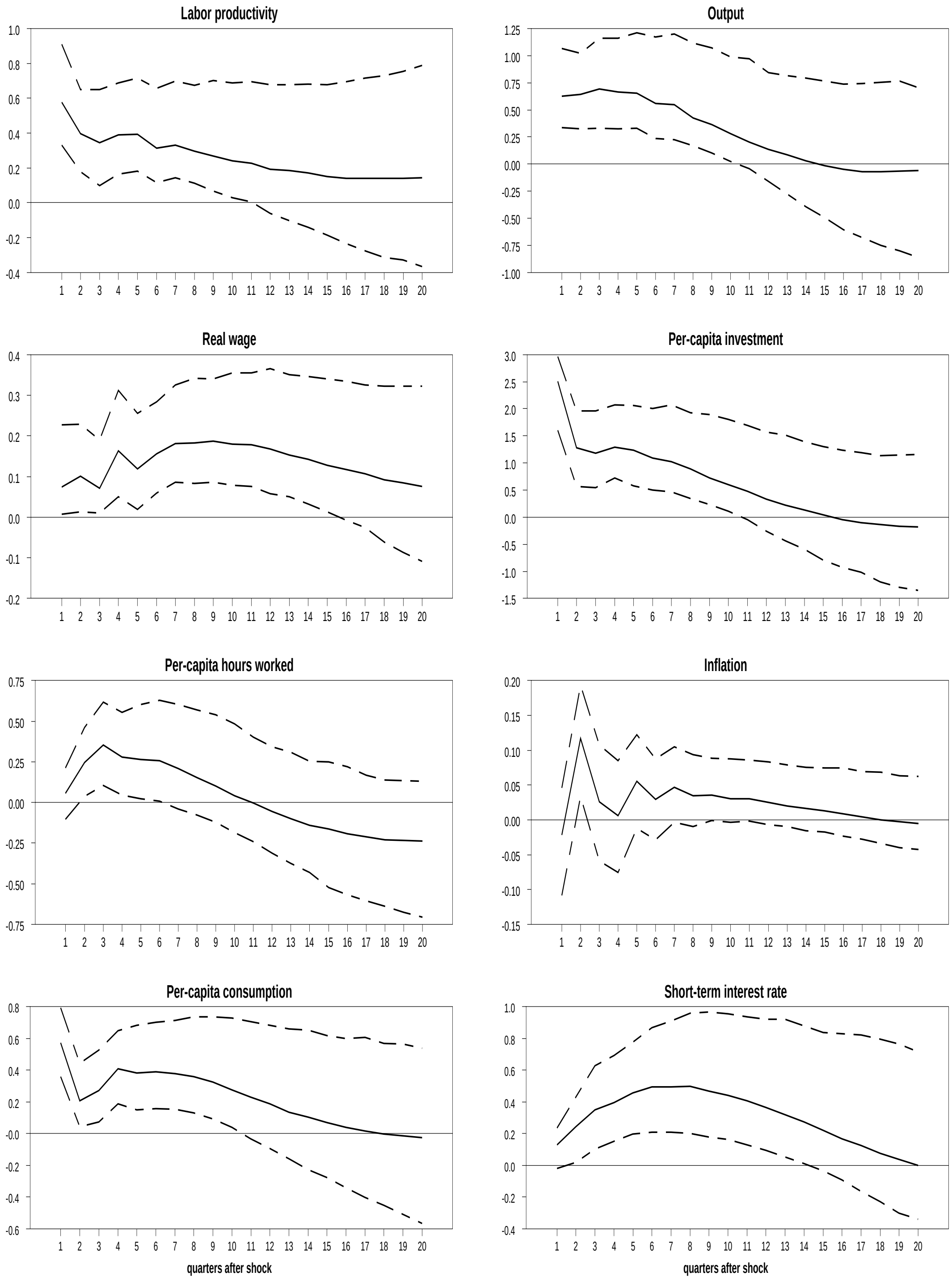

Fig. 3A Impulse responses to positive technology shock (NR identification): United States

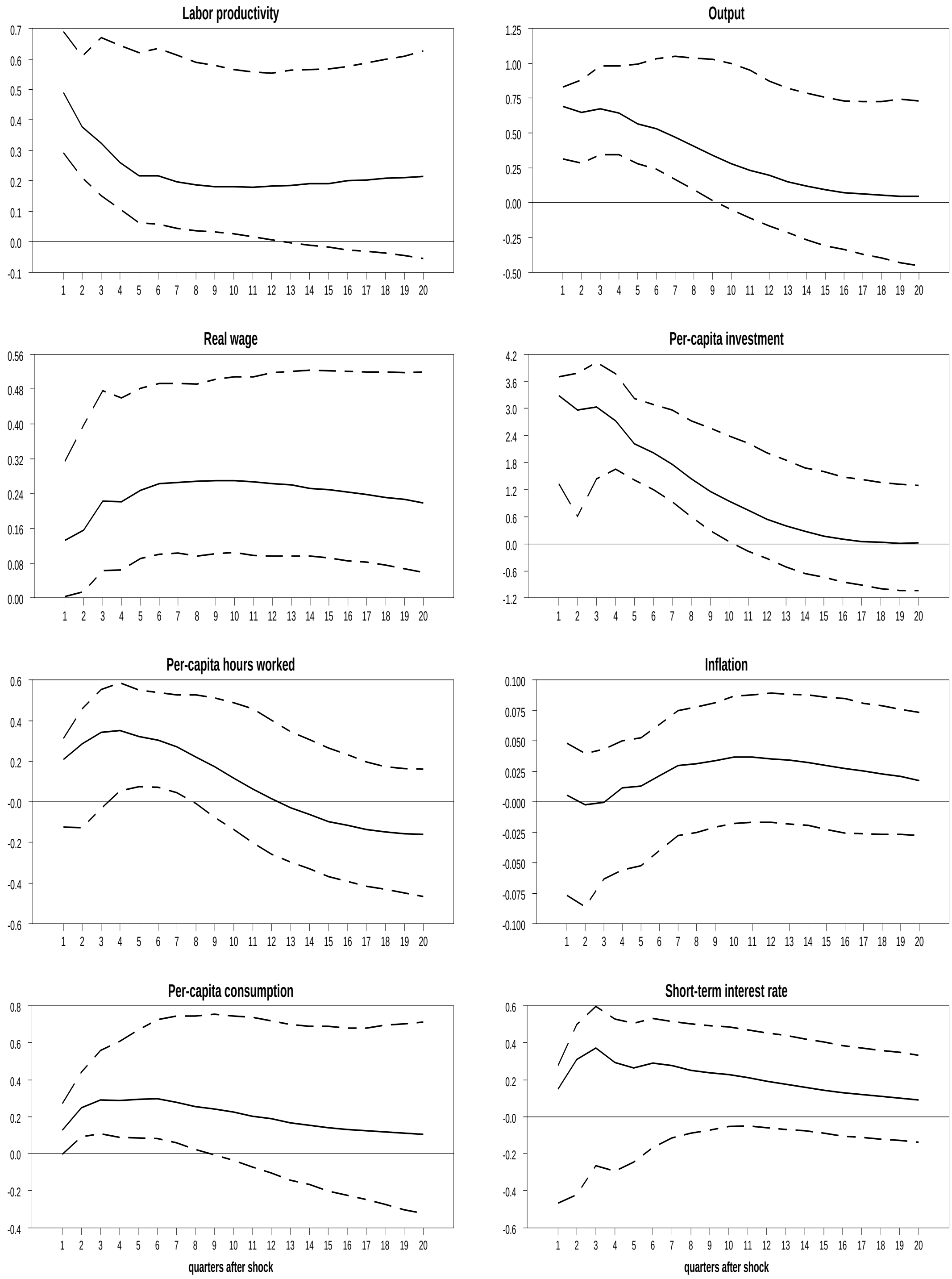

Fig. 3B Impulse responses to positive technology shock (NR identification): Japan

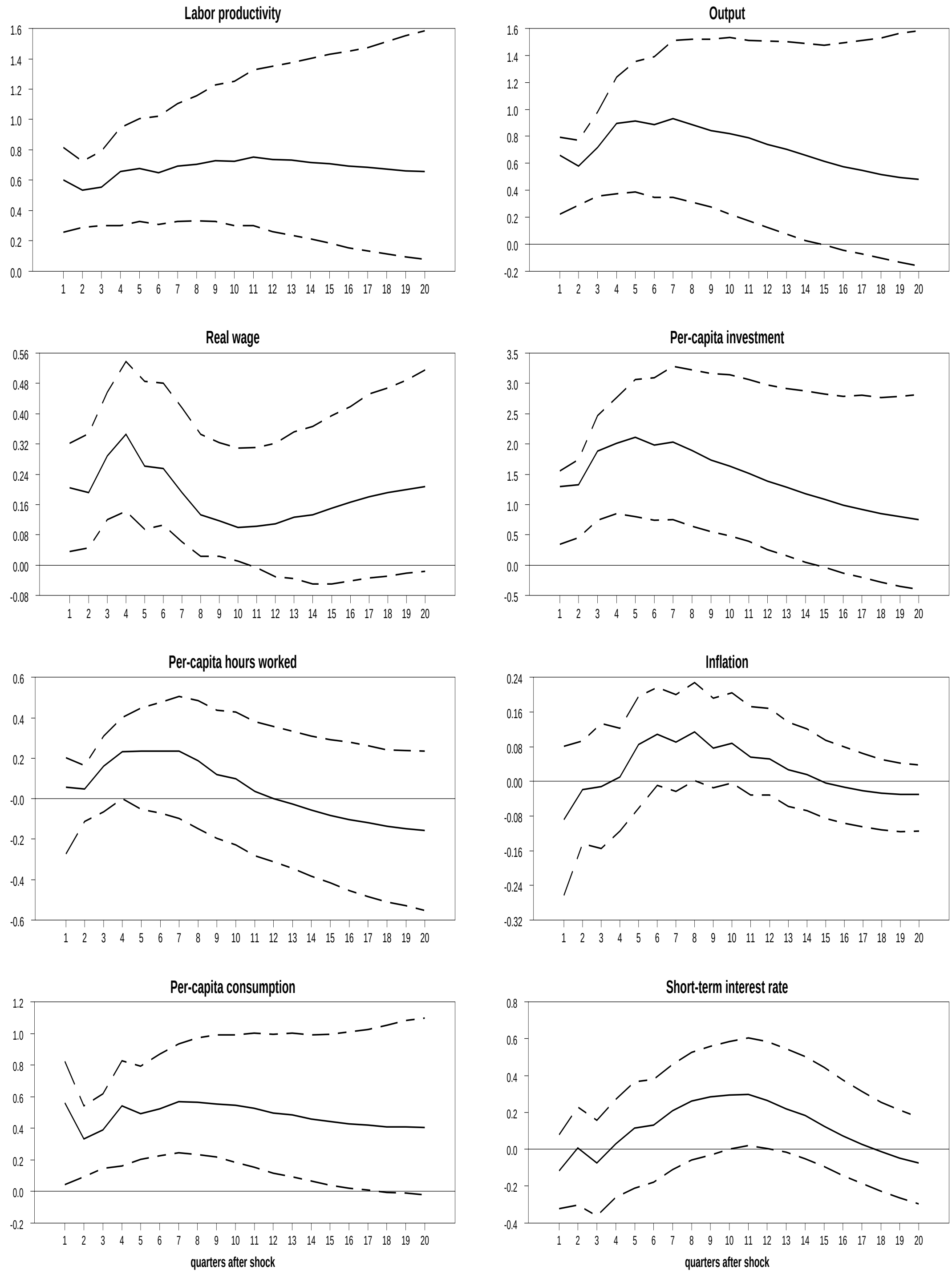

Fig. 3C Impulse responses to positive technology shock (NR identification): West Germany

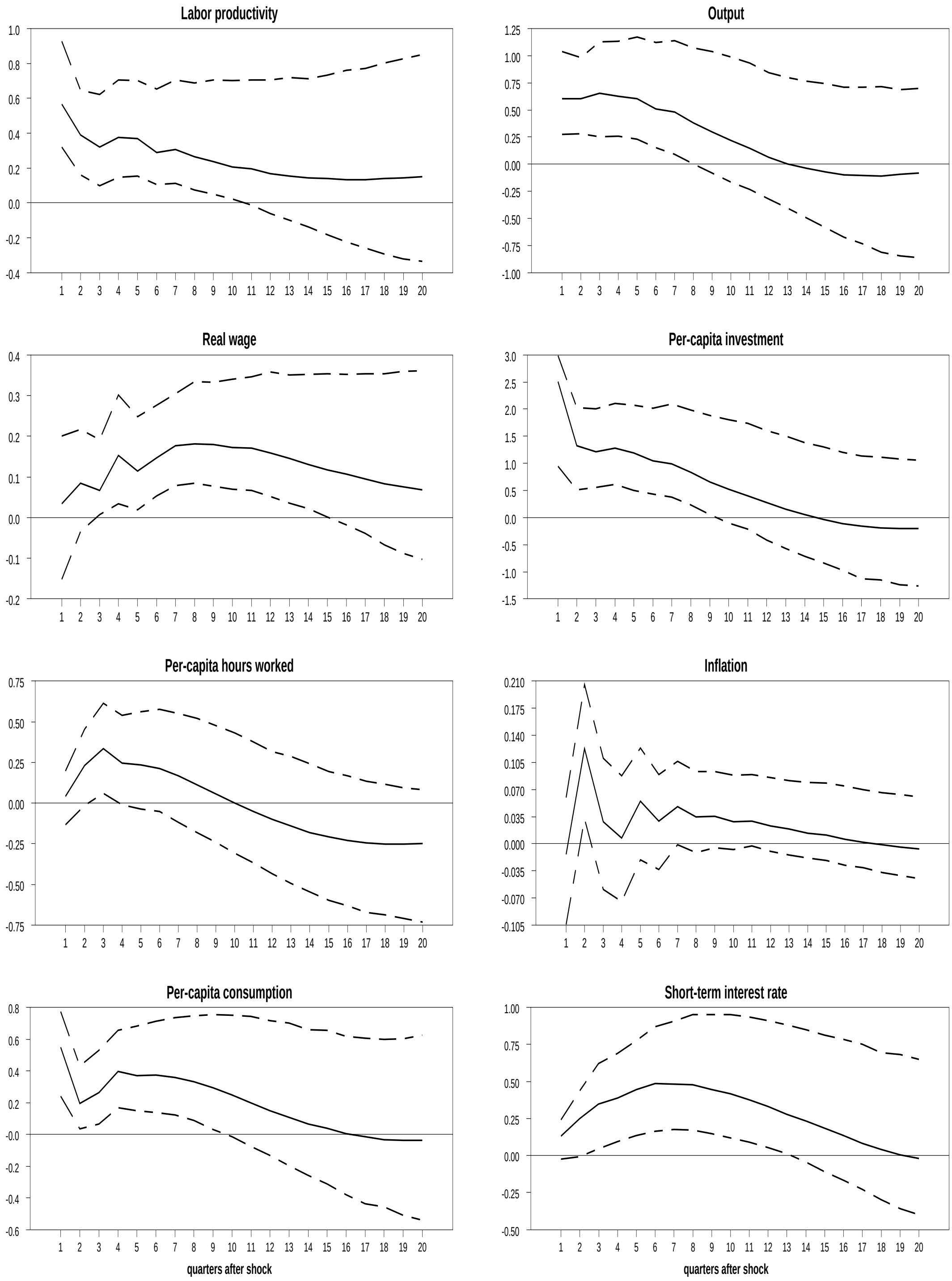

Fig. 4A Distribution of impact responses (RBC identification): United States

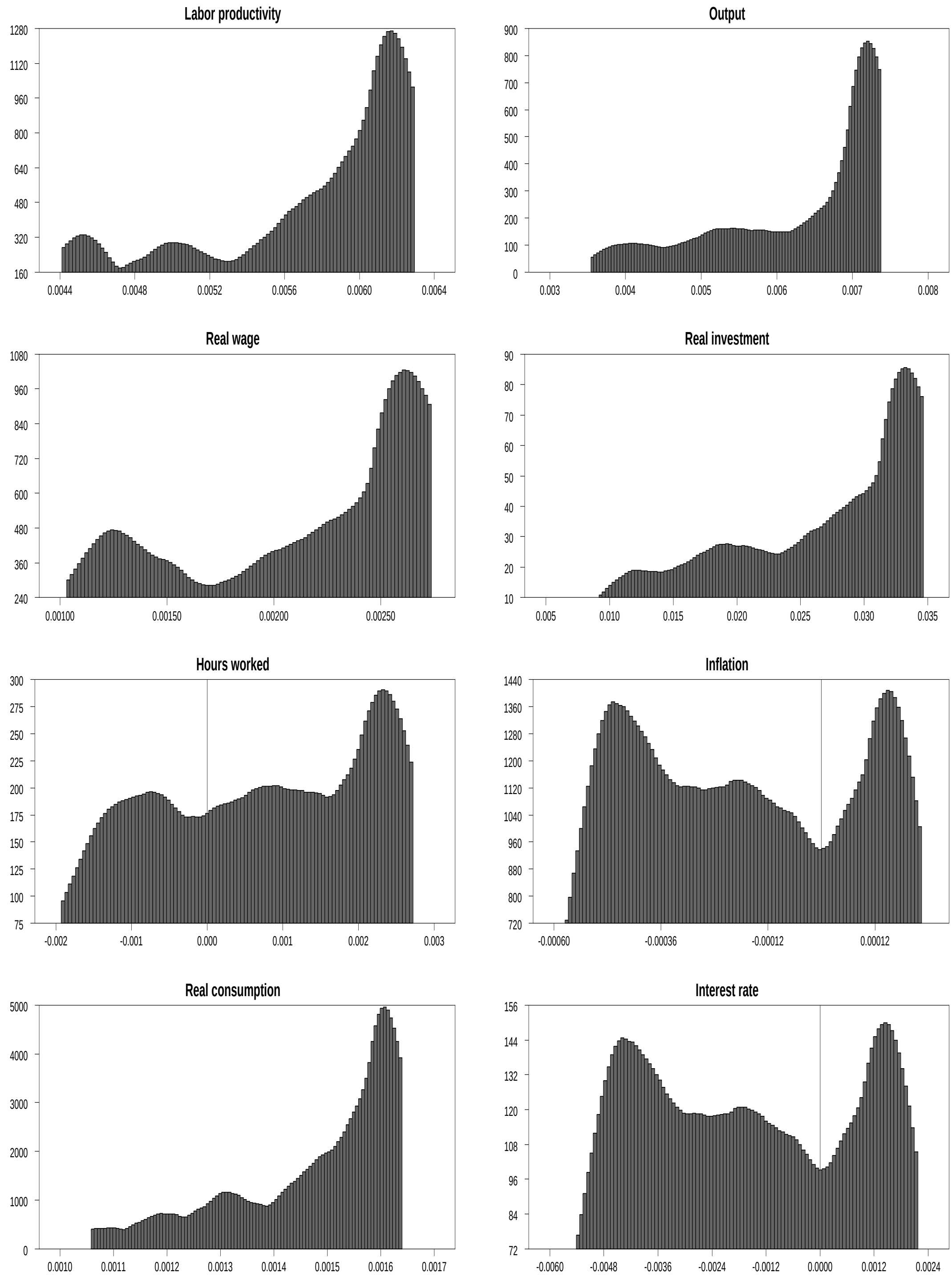

Fig. 4B Distribution of impact responses (RBC identification): Japan

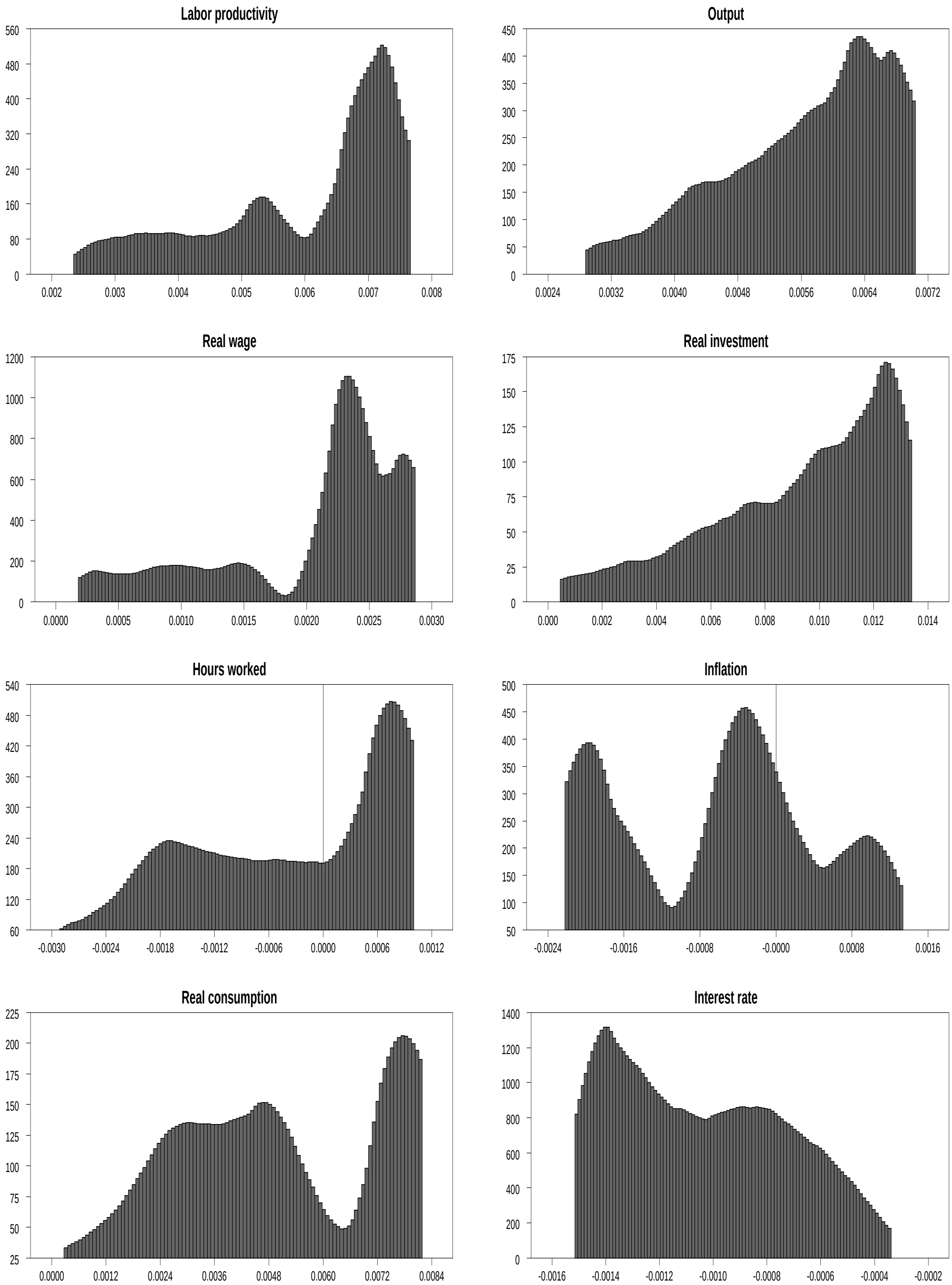

Fig. 4C Distribution of impact responses (RBC identification): West Germany

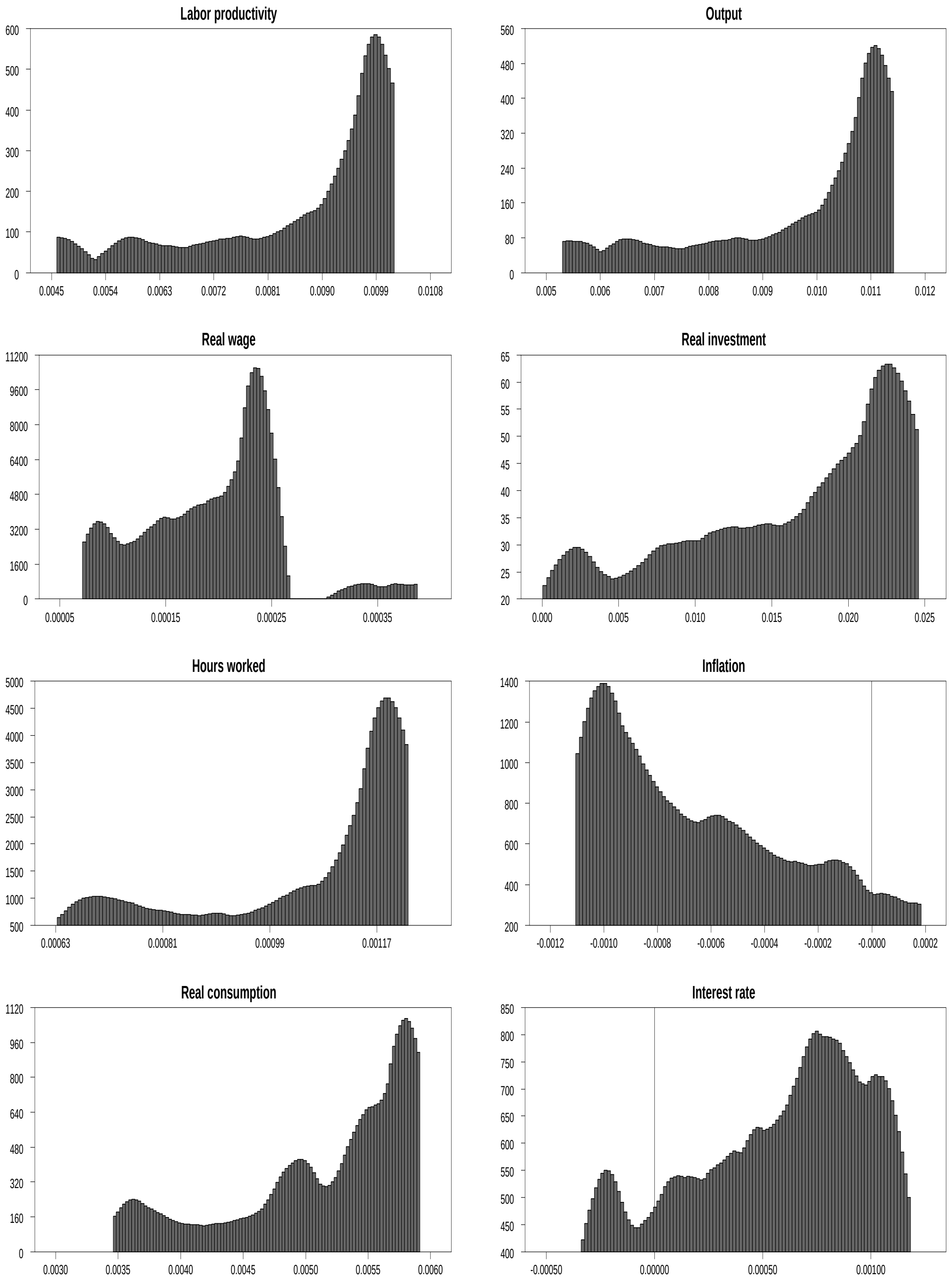

Fig. 5A Impulse response to positive labor increasing / decreasing technology shock: United States

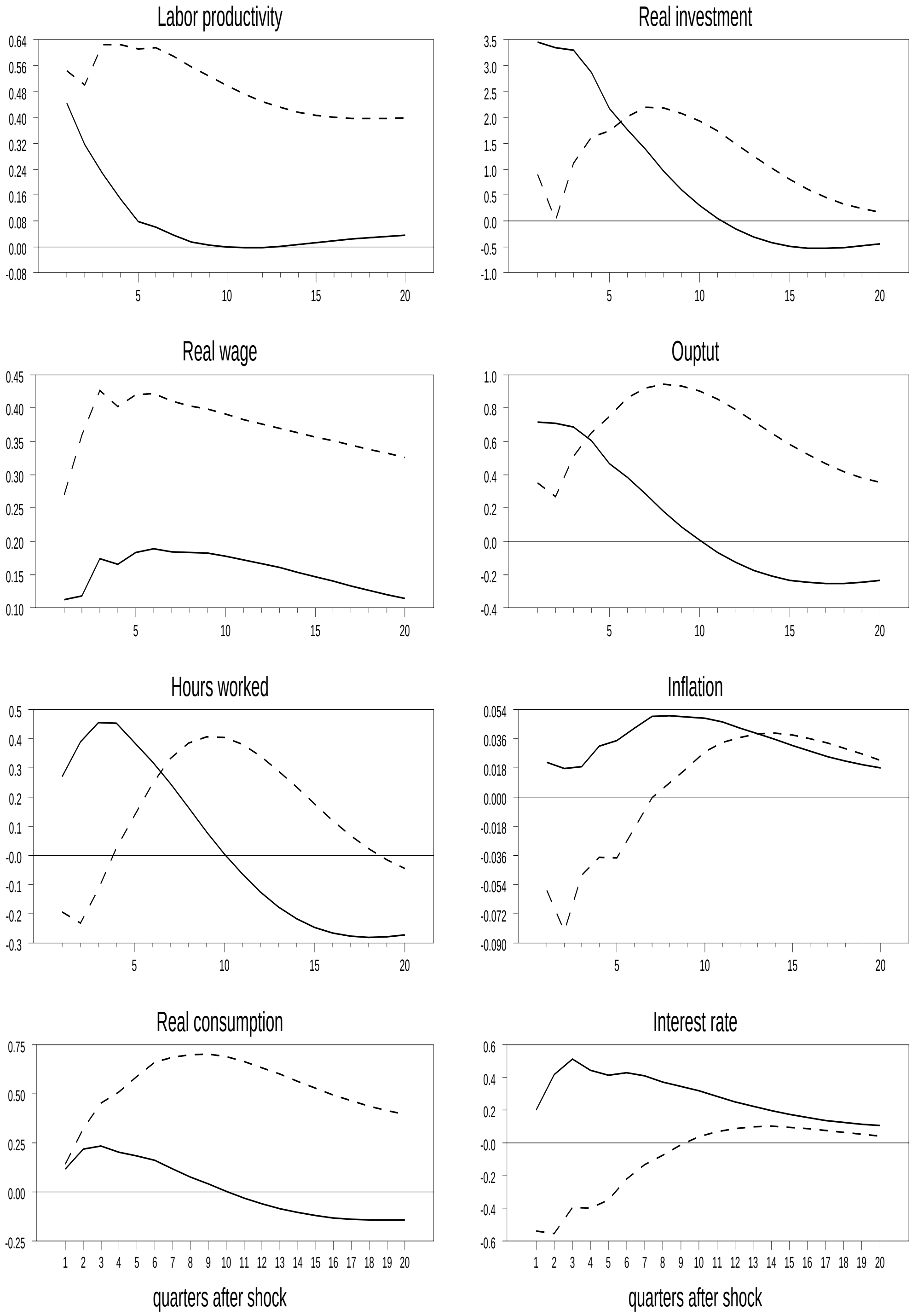

Fig. 5B Impulse response to positive labor increasing / decreasing technology shock: Japan

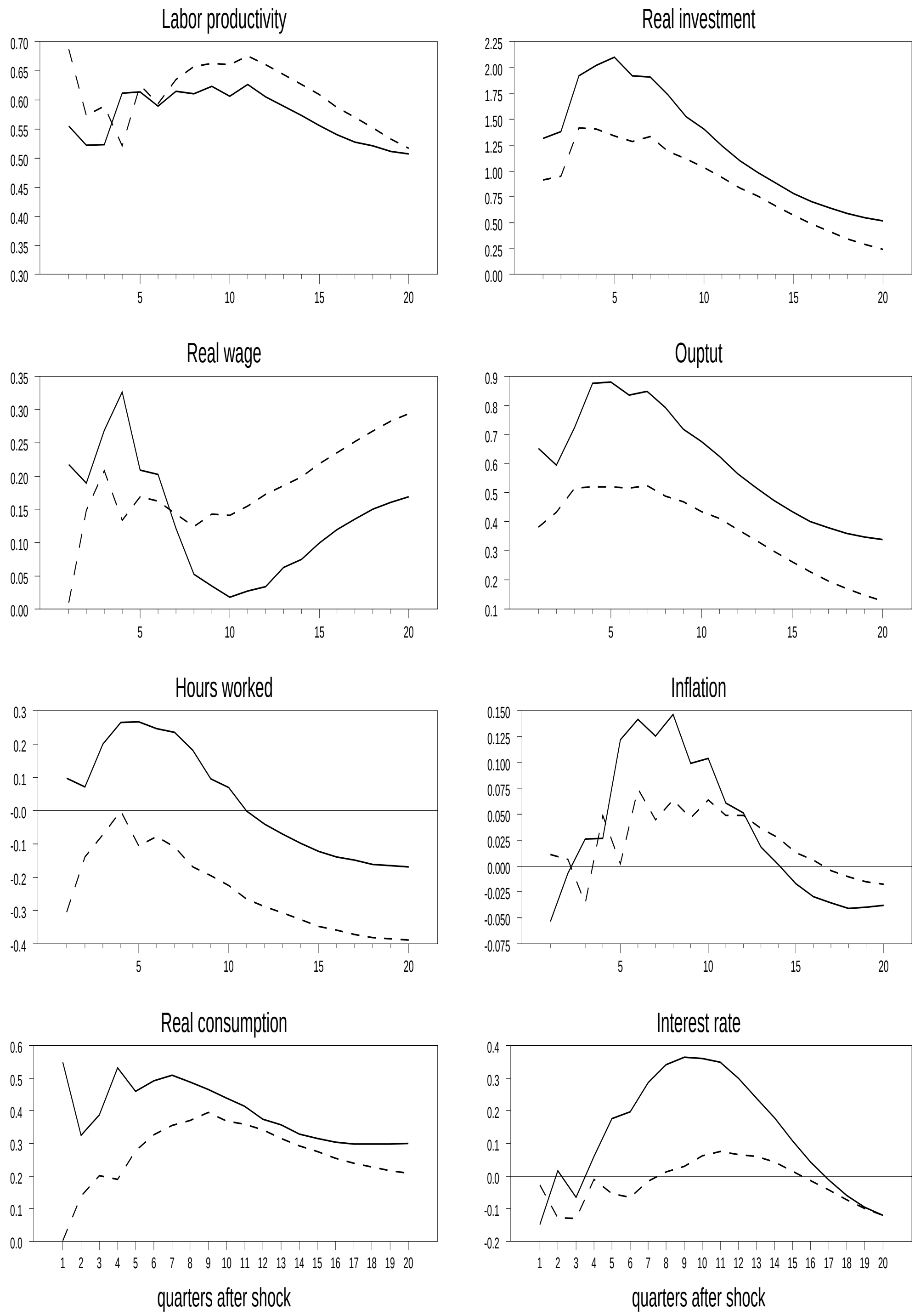

Fig. 5C Impulse response to positive labor increasing / decreasing technology shock: West Germany

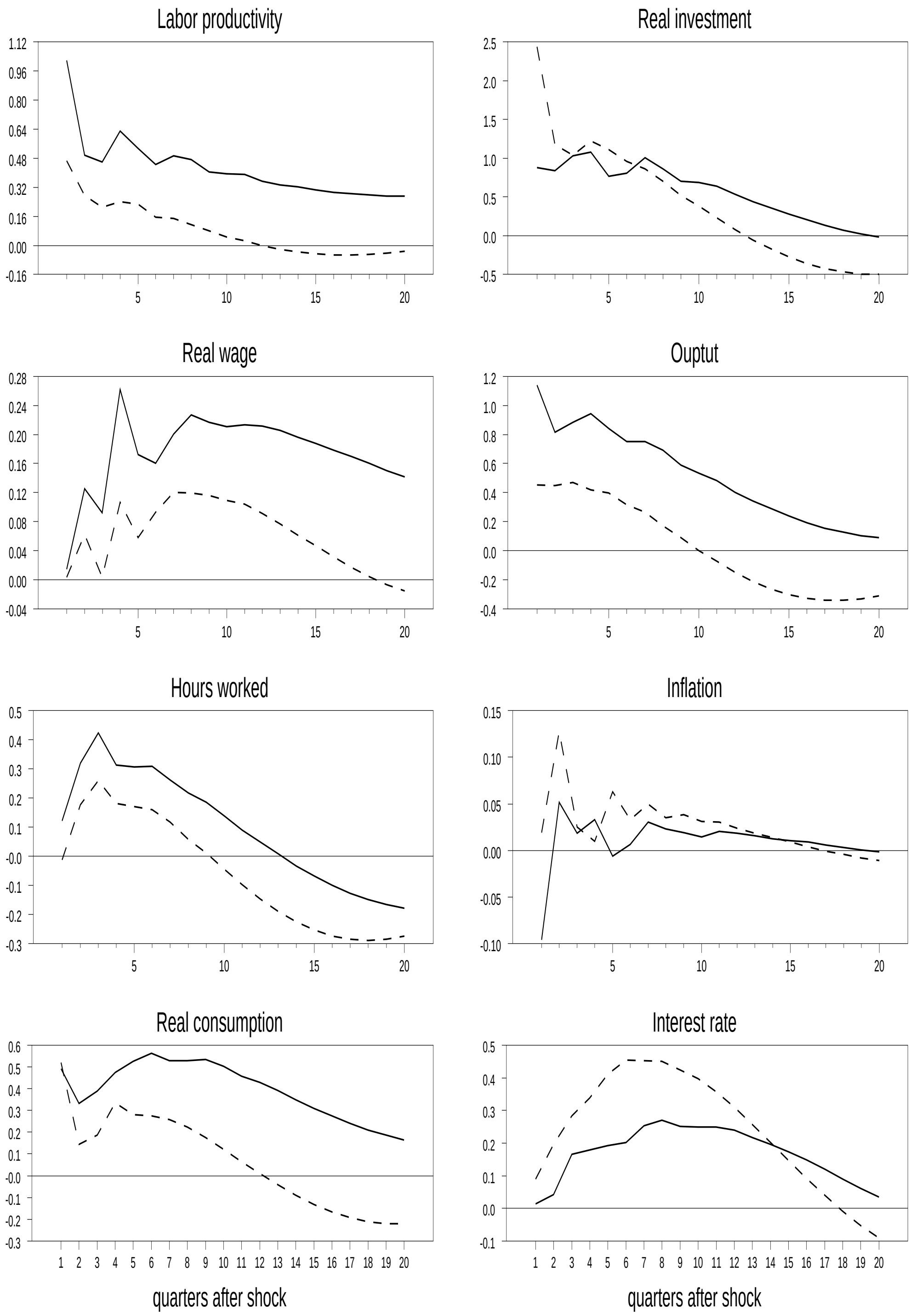

Fig. 6A Variance decomposition (RBC): U.S.

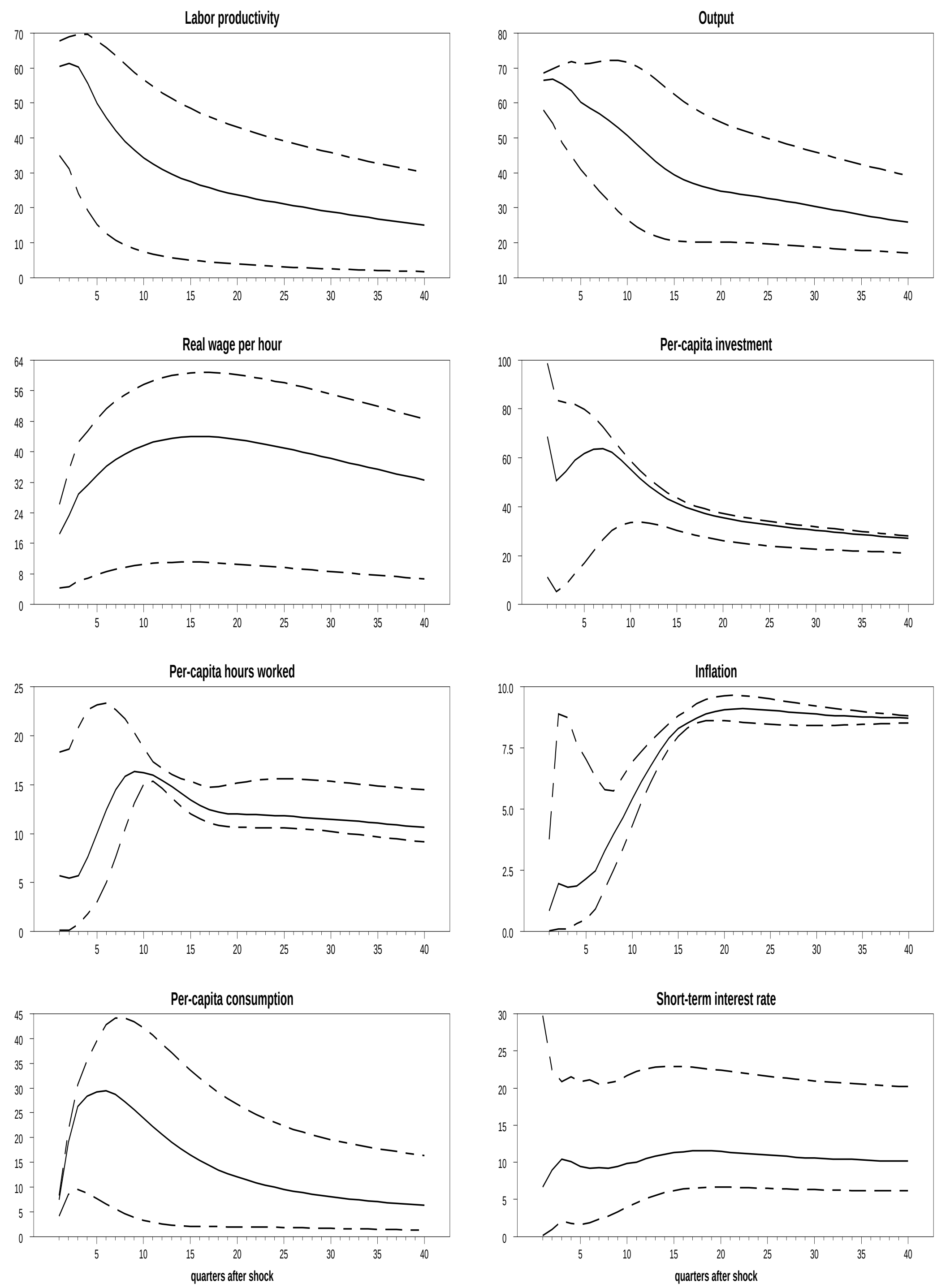

Fig. 6B Variance decomposition (RBC): Japan

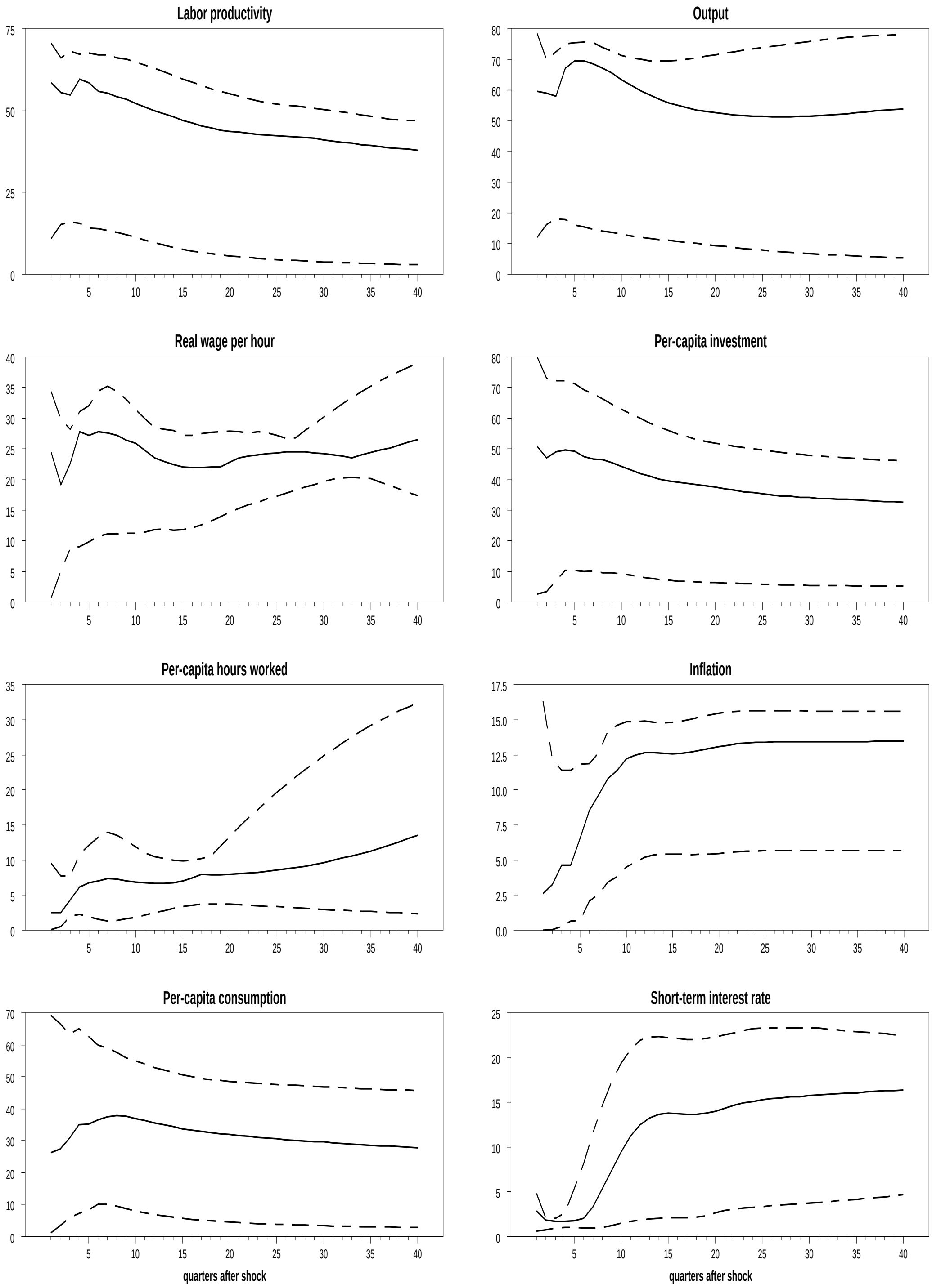

Fig. 6C Variance decomposition (RBC): West Germany

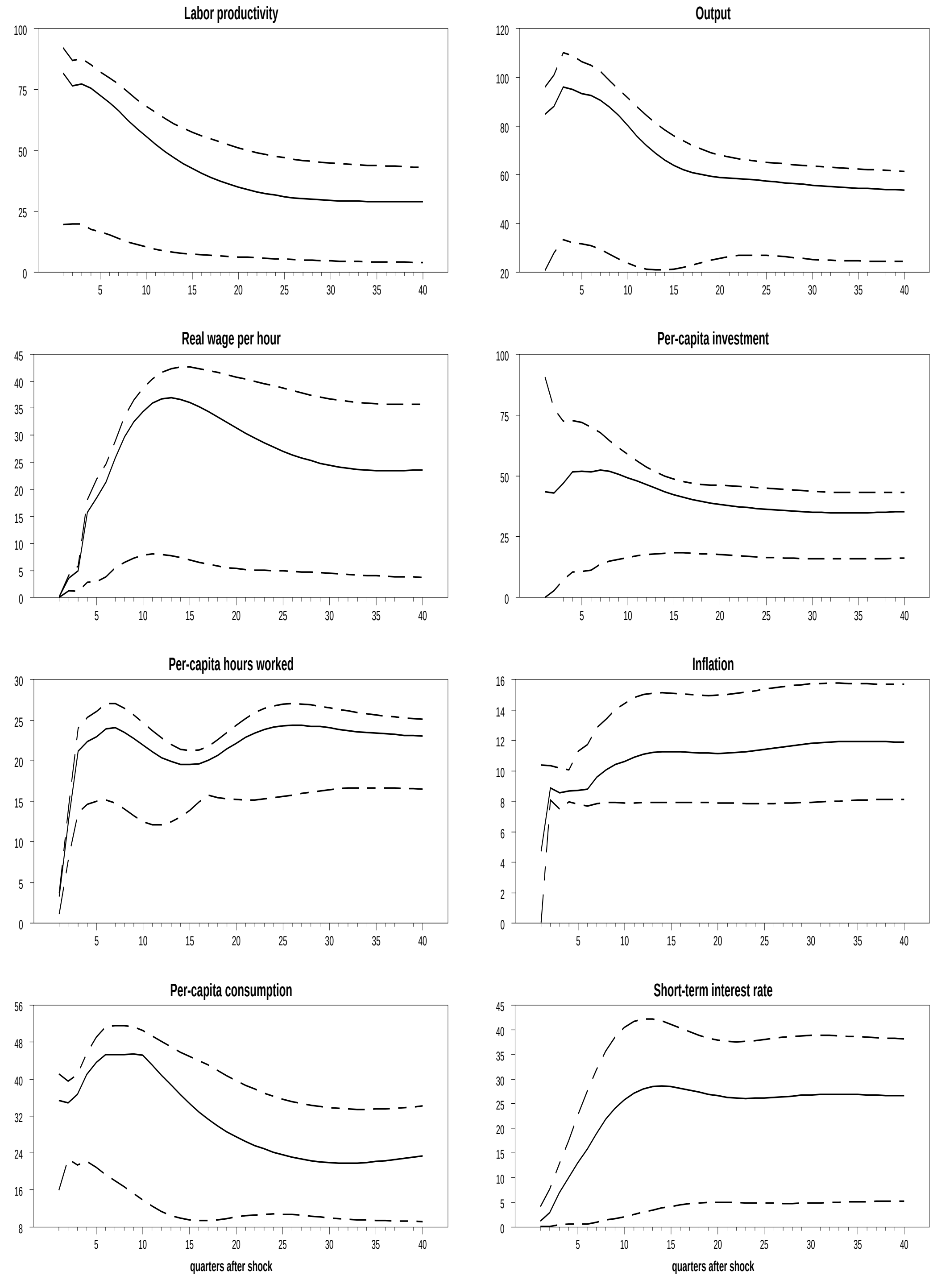

Fig. 7A Impulse responses: RBC model

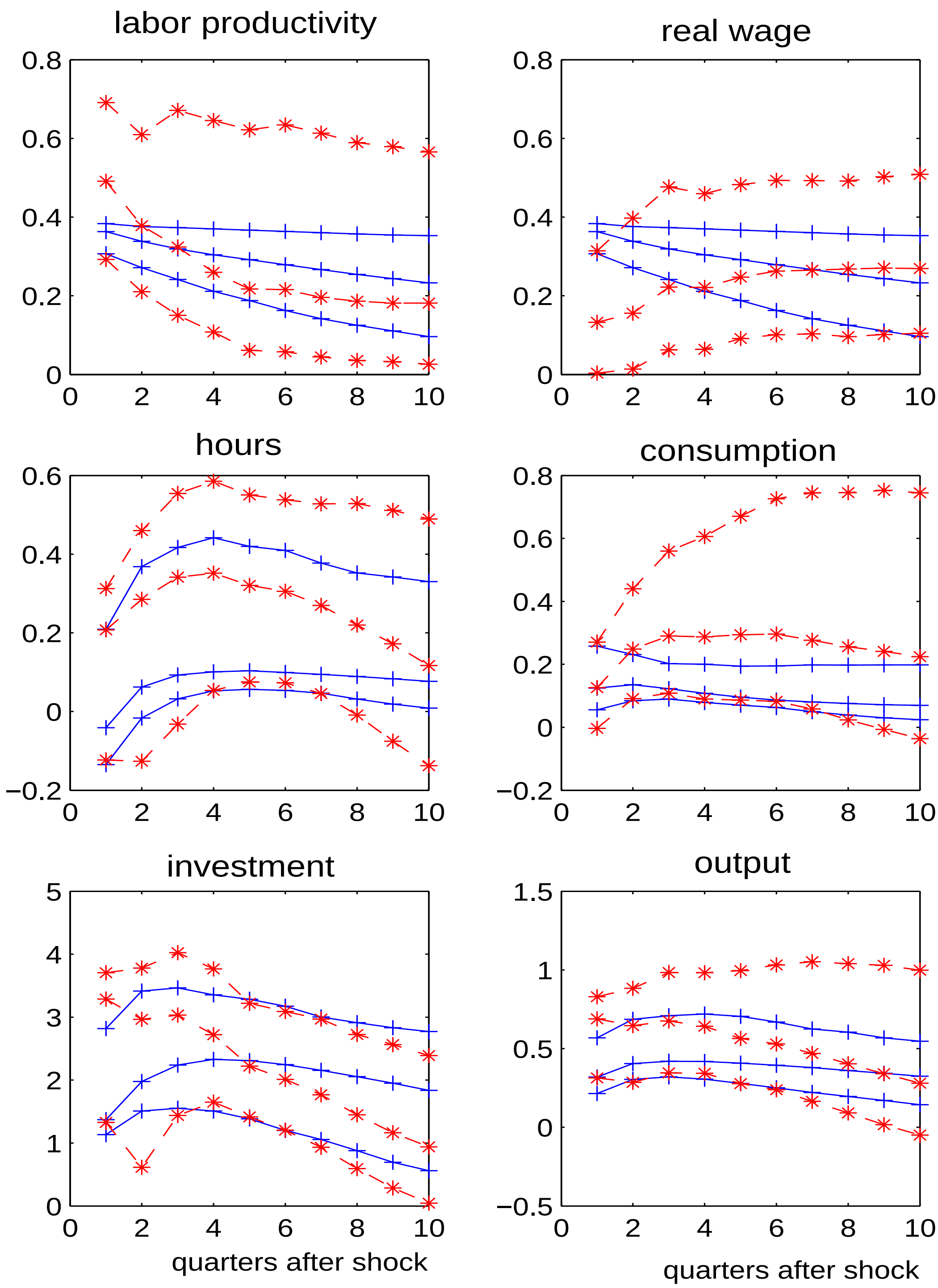

Fig. 7B Parameter distributions: RBC model

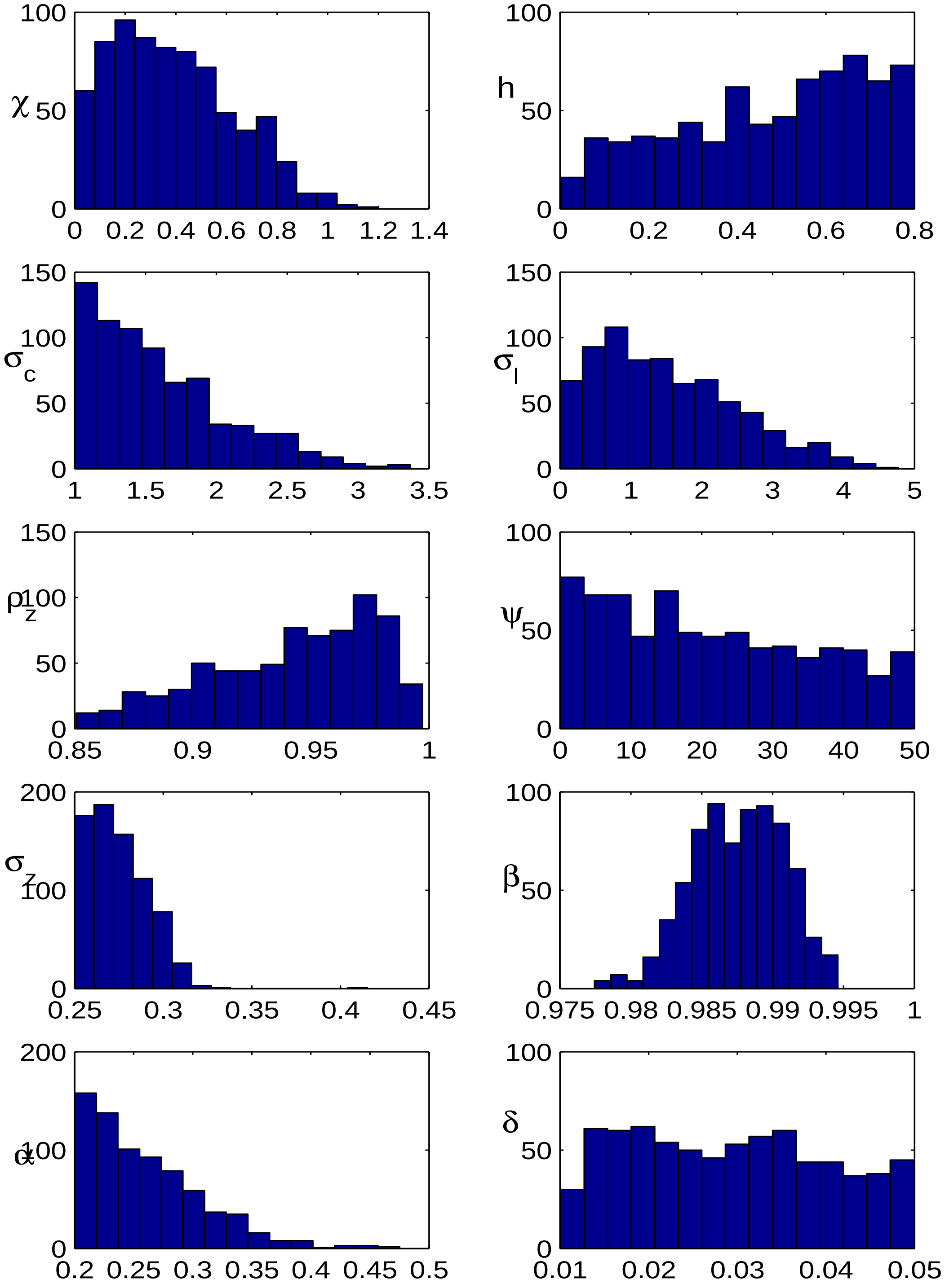

Fig. 8A Impulse responses: NR model

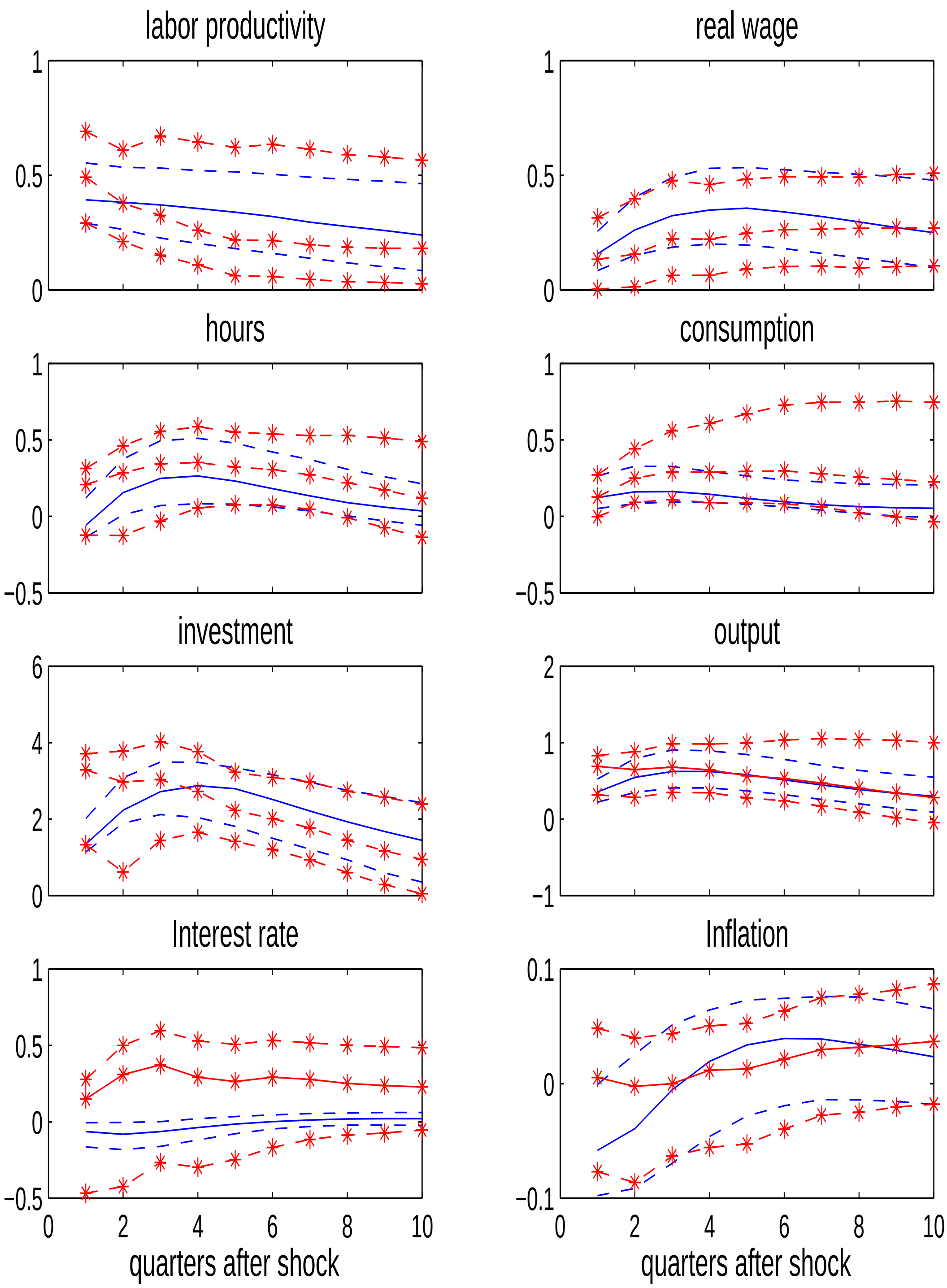

Fig. 8B.1 Parameter distributions: NR model (1)

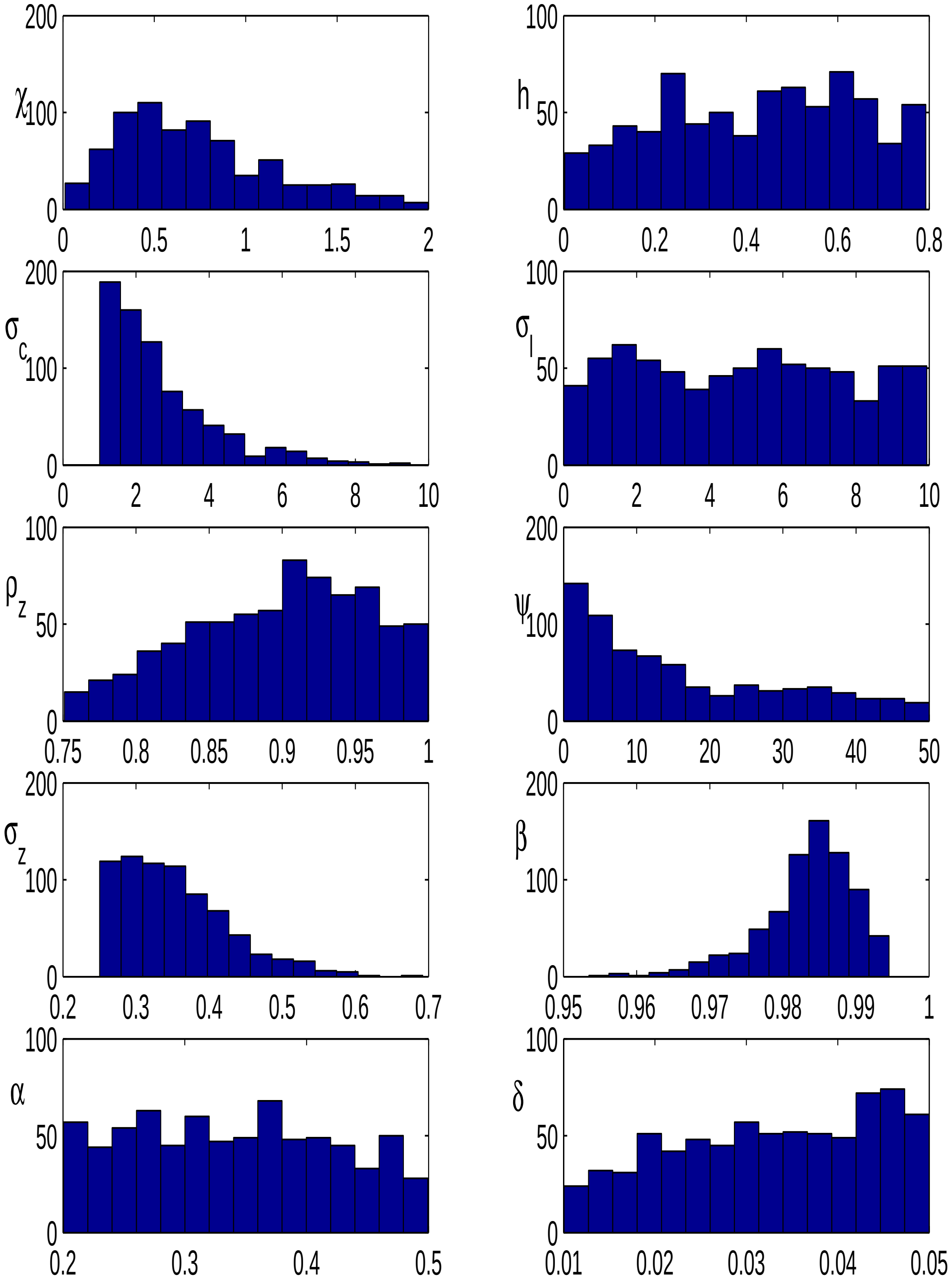

Fig. 8B.2 Parameter distributions: NR model (2)

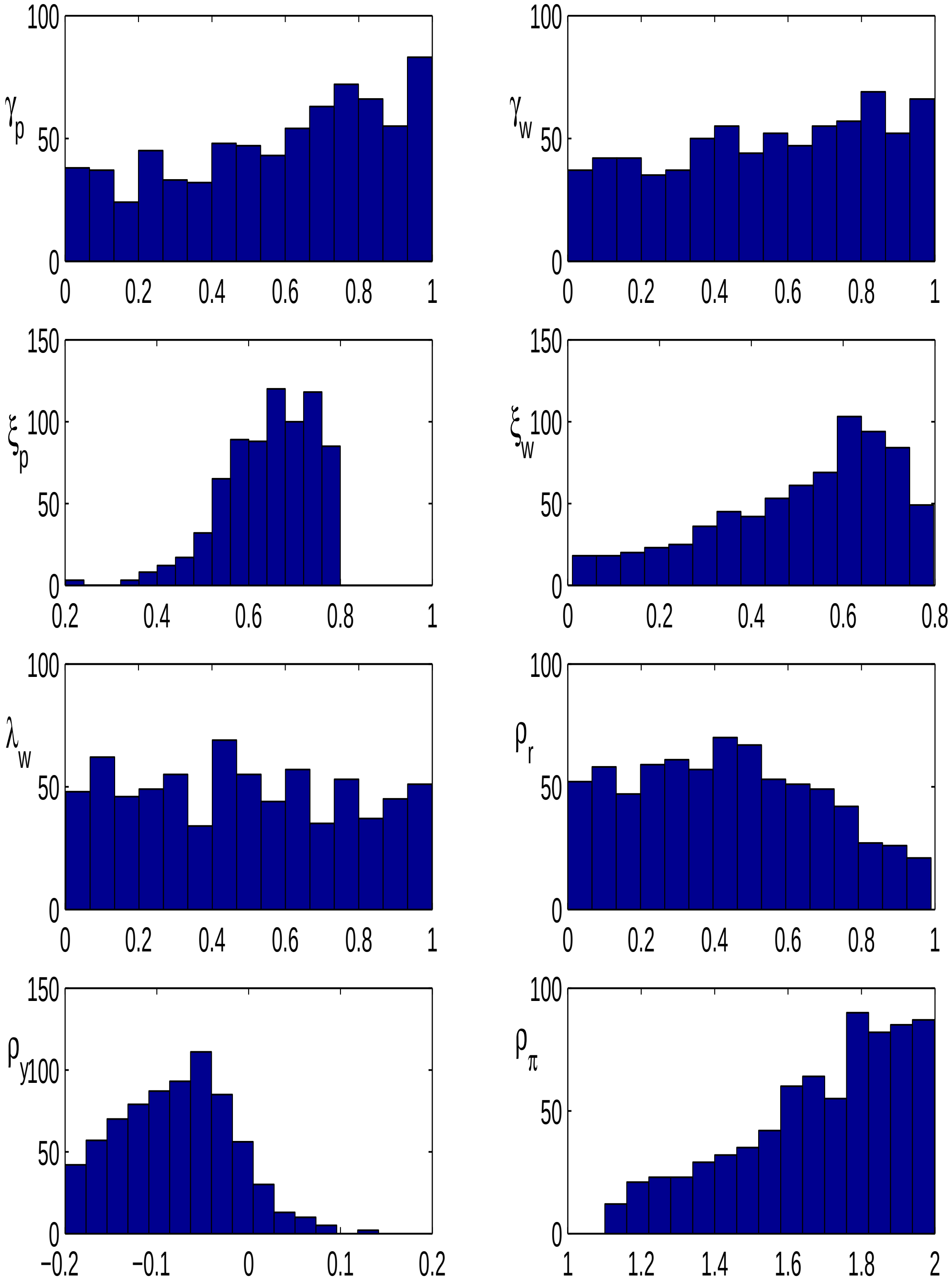

Fig. A2.1 Data: United States

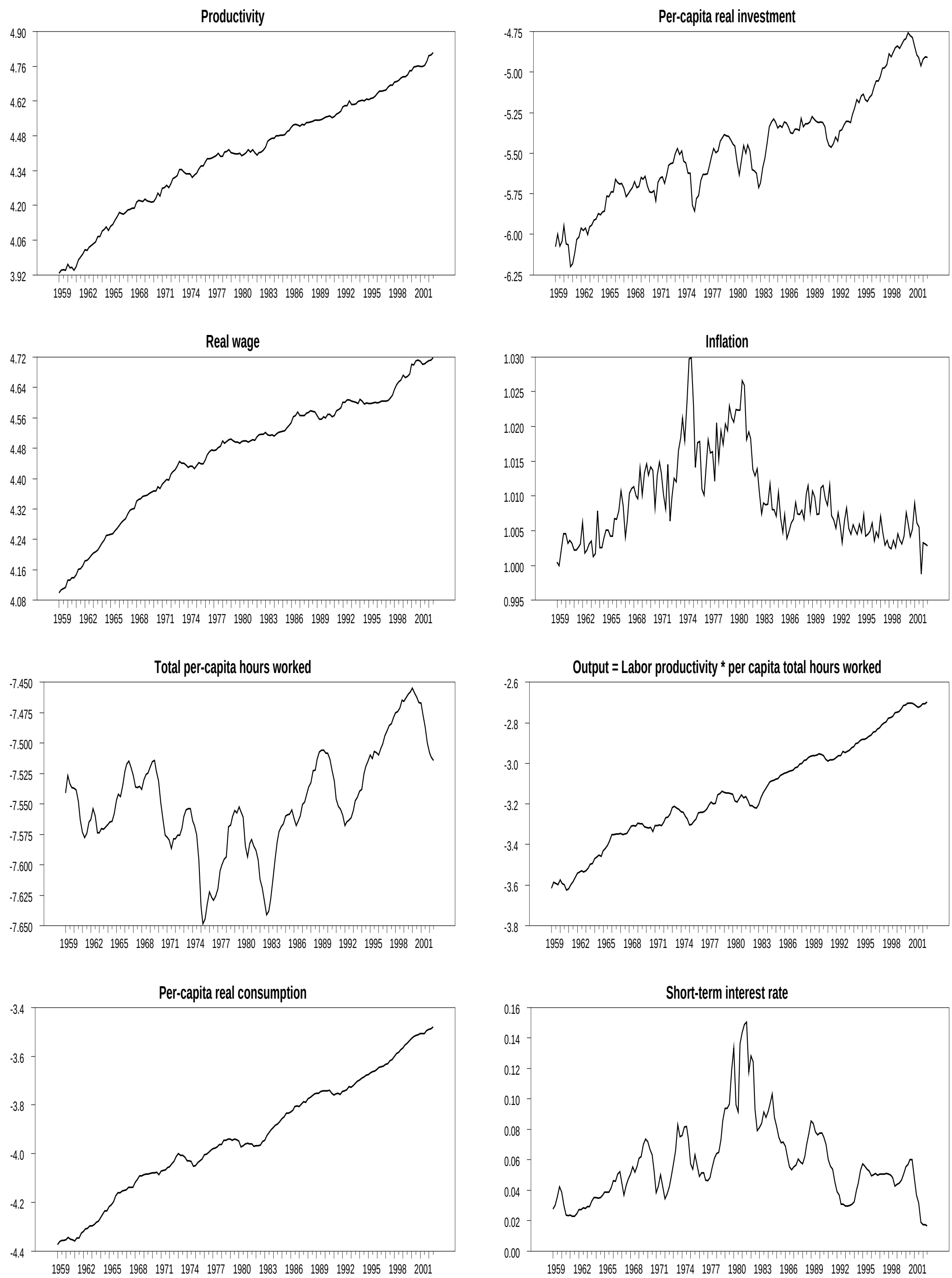

Fig. A2.2 Data: Japan

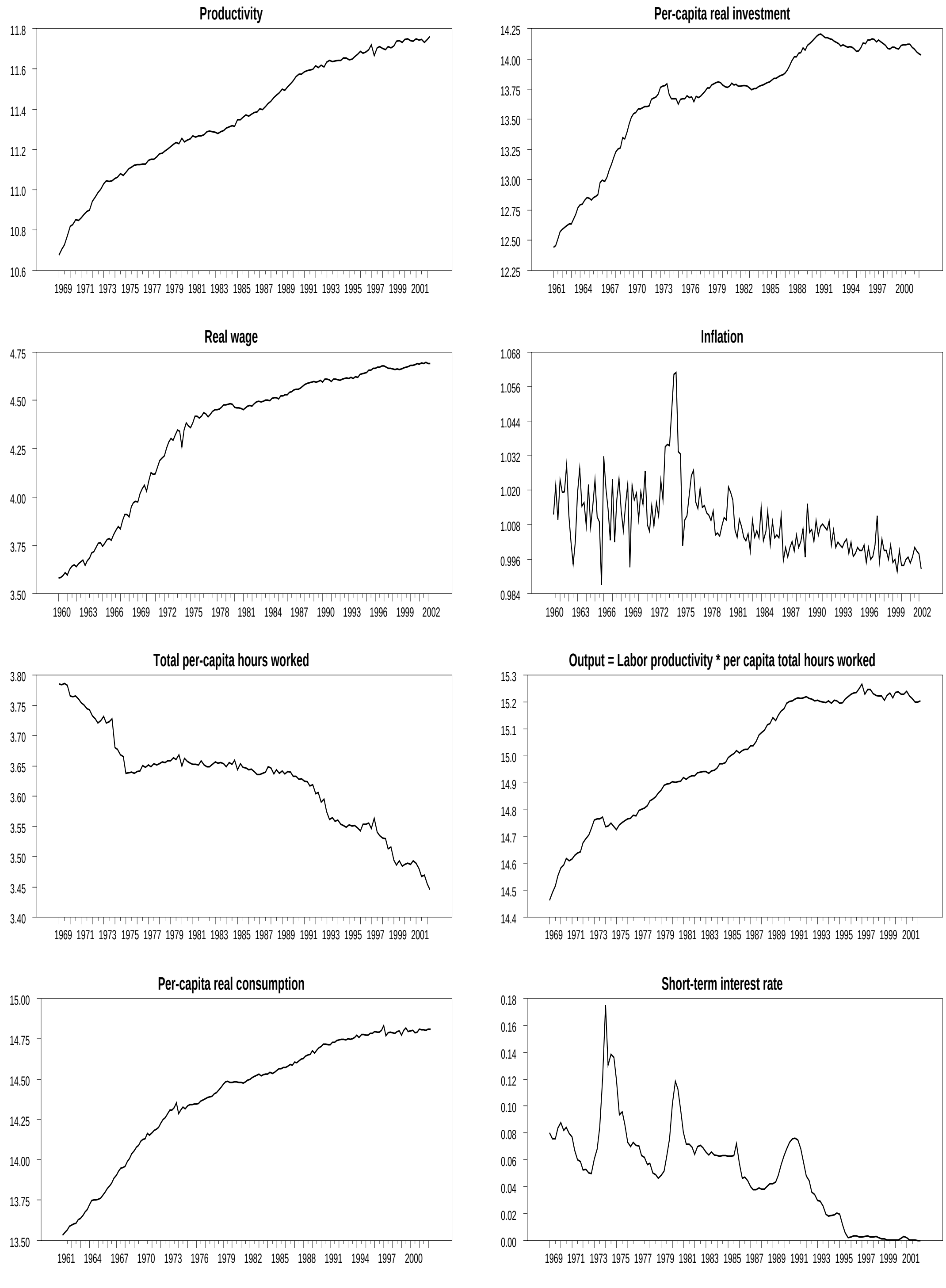

Fig. A2.3 Data: West Germany