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Abstract

Recent empirical studies using infinite horizon long-run restrictions question the validity of the technology-driven real business cycle hypothesis. These results have met with their own controversy, stemming from their sensitivity to changes in model specification and the general poor performance of long run restrictions in Monte Carlo experiments. We propose a alternative identification that maximizes the contribution of technology shocks to the forecast error variance of labor productivity at a long, but finite horizon. In small samples, our identification outperforms its infinite horizon counterpart by producing less biased impulse responses and technology shocks that are more highly correlated with the technology shocks from the underlying model. For U.S. data, we show that the negative hours response is not robust to allowing a greater role for non-technology shocks in the forecast error variance share at a ten year horizon. [JEL: C32, C50, E32]

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1 Introduction

The notion that technological innovations are the pre-eminent force behind business cycle fluctuations has circulated in the macroeconomic literature for some time. This view has recently come under fire in empirical studies, notably Galí (1999), that identify technology shocks in VARs using long-run restrictions.[1] Identification in these models is based on the assumption that technology shocks are the sole impetus behind the persistence in labor productivity. Specifically, identification requires that the unit root in labor productivity arise exclusively from technological innovation. Applied to the data, this assumption predicts a decline in labor hours following a positive innovation in technology, apparently contradicting the theoretical predictions of a broad class of real business cycle (RBC) models.[2]

This result has initiated some controversy, with some studies offering conflicting evidence based on alternative specifications of the non-productivity component of Galí's empirical model. Much of this debate has arisen around the assumption regarding the stationarity of hours and its relation to the short-run negative response to technology shock.[3] This paper, however, focuses on the identifying assumption regarding the estimated long-run *productivity* process, which has received considerable scrutiny in the literature but, to our knowledge, little resolution.

By their nature, long-run restricted structural vector autoregression (LSVAR) models are subject to the generic criticism that restrictions on infinite-order lag polynomials are ill suited to estimation in samples of realistic proportions [see, for example, Sims (1972), Faust (1996), Faust and Leeper (1997)]. The intuition is that finite samples generate imprecise measures of the VAR moving-average parameters at very long horizons, which when relied on for identification purposes, translate into imprecise and potentially spurious inference. Using Monte Carlo methods, Erceg, Guerrieri, and Gust (EGG, 2004) and Chari, Kehoe, and McGrattan (CKM, 2005) assess the extent of these small sample estimation problems. These papers simulate repeated small samples

[1] Others have critcized the so-called real business cycle models on the grounds of not fitting the data well [Watson (1993)].

[2] Basu, Fernald, and Kimball (2004) and Shea (1998) used different techniques to identify technology. These studies also find that hours contract on impact in response to a positive technology shock.

[3] Christiano, Eichenbaum, and Vigfusson (CEV, 2004) argue that labor, if assumed stationary, responds to a technology shock positively on impact. They contend that *per capita* labor is bounded and cannot have a unit root. In a related paper, Francis and Ramey (2004a, 2004b) reject a unit root in per capita hours after accounting for demographic components. However, this resulting demographically-adjusted per capita labor series responds negatively to a technology shock. Further, Pesavento and Rossi (forthcoming) employ near-unity approximations to construct robust confidence intervals for the impulse responses. They find that hours respond negatively on impact.

from variations of the standard RBC model and apply the long-run restriction from Galí (1999) to obtain hypothetical small-sample distributions of the LSVAR impulse responses. CKM finds that the small-sample LSVAR impulse responses are qualitatively inaccurate in comparison with the theoretical impulse responses, while EGG obtain impulse responses that are somewhat biased but qualitatively similar to the theoretical model's impulse responses.

In addition to these econometric shortcomings, there may be a practical argument against the theoretical assumption that technology is the only process influencing the long-run behavior of labor productivity. Francis and Ramey (forthcoming) and Uhlig (2003) incorporate capital tax shocks, which may also contribute to the variance of long-run labor productivity. In this case, long-run exclusivity restrictions may be inappropriate to obtain a proper measure of the technology shock from the data.

We offer an alternative identification approach that aims at these shortcomings while maintaining the association of long-run productivity with technology. Specifically, we identify the technology shock as that which produces the maximum forecast error variance (MFEV) share in labor productivity at a long, finite horizon. Choosing a sufficiently long horizon (such as ten years) allows us to focus on the variance in productivity at horizons beyond typical business cycles. At the same time, our approach has several potential advantages over the conventional long-run approach. First, by focusing on a finite horizon, we hope to gain estimation precision over the long-run restriction which relies on much longer horizon parameter estimates. Second, under certain assumptions, inference based on the MFEV specification is robust to either unit root or near-unit root behavior in productivity.[4] Finally, in place of the restriction that there is a unit root in productivity driven *exclusively* by technology, our approach requires only that the long-run forecast-error variance for productivity be *dominated* by the technology shock. Thus, we allow for other (albeit less dominant) shocks to influence labor productivity in the long-run.

In the next section, we present the MFEV identification approach analytically and discuss its differences with the LSVAR approach in more detail. We then compare the small sample

[4] A shortcoming of LSVAR approach to techonology shocks is that it does not appropriately account for uncertainty regarding near-unit root alternatives. Unit root tests are well understood to have low power in finite samples [Blough (1992), Cochrane (1991), Christiano and Eichenbaum (1990), Stock (1990), Sims (1989)]. Also, classical confidence intervals are inappropriate in the presence of uncertainty about unit roots [Sims and Zha (1999) and Sims and Uhlig (1991)]. Thus, it follows that a specification of long-run productivity which is robust to near-unit root behavior should obtain better coverage.

performances of the MFEV and LSVAR approaches using Monte Carlo methods and a standard RBC model. We also compute the correlations of the estimated technology shocks with the realized shocks from the RBC model. Although the performance of the two identification approaches depends on the parameterization of the theoretical model, we find that the MFEV often performs significantly better and never performs worse than the LSVAR.

In the remainder of the paper, we apply the MFEV approach to postwar U.S. data and examine the robustness of the LSVAR findings to our relaxation of the original identifying assumption. Estimating the MFEV model directly predicts a negative short-run response in hours to a technology shock, supporting Gali's original finding, albeit with greater statistical precision than in the LSVAR model. Robustness analysis shows, however, that the sign prediction for hours is not robust to a further relaxation in the identifying assumption. In particular, we find that a positive hours response is predicted when we allow a modest increase in the role of non-technology shocks in the ten year forecast error variance of productivity.

2 Identification

In this section, we review the method of using long-run restrictions for identifying technology shocks and introduce an alternative identifying restriction on the share of productivity's long-horizon forecast-error variance due to technology. The identifying assumption in technology LSVARs comes from a class of RBC models in which log labor productivity x_t can be decomposed into two orthogonal components, technology, z_t, and non-technology, $\varepsilon_t^{non-tech}$, in the following manner:

$$x_t = z_t + \varepsilon_t^{non-tech}. \tag{1}$$

Since all processes but technology are assumed stationary, the unit root in productivity must arise from z_t.[5] This condition provides the foundation for both the standard long-run identification and our finite-horizon identification.

[5] This arises from the steady-state condition $X = W = \alpha Z \left(\frac{k}{N}\right)^{1-\alpha}$ relating labor productivity X to wages W, where k is the ratio of capital to technology, N is labor, α is the marginal productivity of labor, and Z is the level of technology. The relation (1) resembles the Beveridge-Nelson decomposition, where $\varepsilon_t^{non-tech}$ can be thought of as a composite non-technology shock including fiscal, monetary, and tax shocks.

2.1 Infinite-Order Long-Run Identification

We assume that the data generating process can approximated by the following linear model:

$$A(L)y_t = \varepsilon_t, \tag{2}$$

where y_t is an $n \times 1$ vector of macroeconomic time series, $A(L) = \sum_{i=0}^{p} A_i L^i$ is a matrix polynomial in the lag operator, L, ε_t is a structural innovation, and $E(\varepsilon_t \varepsilon_t') = I$. To estimate this model using data, we begin with the reduced-form VAR:

$$B(L)y_t = \mu_t, \tag{3}$$

where $B(L) = \sum_{i=0}^{p} B_i L^i$, $B_0 = I$, and $E(\mu_t \mu_t') = \Omega$. The goal is to find a rotation of the moving-average representation of this VAR,

$$y_t = C(L)A_0^{-1}A_0\mu_t,$$

$(C(L) = B(L)^{-1})$ which identifies the i.i.d. structural shocks of model:

$$\varepsilon_t = A_0\mu_t,$$

where A_0 is the contemporaneous parameter matrix. Identification is accomplished by imposing a sufficient number of restrictions on the system; $\frac{n(n-1)}{2}$ restrictions are required to fully identify the structural form (fewer less restrictions are necessary to identify a single shock). Short-run restrictions often take the form of recursive or non-recursive zero restrictions on A_0. Long-run restrictions place constraints on the effect of the jth shock on the ith variable at an infinite horizon, given by $\left[C(1)A_0^{-1}\right]_{i,j}$, where neutrality implies the restriction $\left[C(1)A_0^{-1}\right]_{i,j} = 0$.

The key identifying assumption in Galí (1999) is that the technology shocks are the only influence on long-run labor productivity. With productivity entering in differences and ordered first in the VAR, this assumption is implemented by restricting the long-run responses to all non-technology shocks to be zero.

Assumption A.1 The unit root in productivity is solely attributable to the technology shock

z. That is,

$$\left[C(1)A_0^{-1}\right]_{i=1,j\neq i} = 0, \tag{4}$$

where $i = 1$ represents labor productivity ordered first and $j \neq i$ indicates all non-technology shocks.

The h-step ahead forecast error associated with an innovation $\varepsilon_{t+h-\tau}$ can then be written as

$$y_{t+h} - \widehat{y_{t,h}} = \sum_{\tau=0}^{h-1} \Theta_\tau \mu_{t+h-\tau}, \tag{5}$$

where Θ_τ are the impulse-generating matrices. Given (5), the h-step ahead forecast error variance share for variable i attributable to shock j is

$$\omega_{ij}(h) = \frac{e_i' \left[\sum_{\tau=0}^{h-1} \Theta_\tau A_0^{-1} e_j e_j' A_0^{-1\prime} \Theta_\tau'\right] e_i}{e_i' \left[\sum_{\tau=0}^{h-1} \Theta_\tau \Omega_\mu \Theta_\tau'\right] e_i}, \tag{6}$$

where e_k is an indicator vector. With this in mind, one can see that (4) implies the following:

Proposition 1 *Under assumption A.1, as h approaches ∞, the forecast-error variance share of productivity attributable to the identified technology shock asymptotes to one ($\lim_{h\to\infty} \omega_{ij}(h) = 1$).*

If productivity is ordered first, the assumption that the long-run response of labor productivity to all non-technology shocks are negligible drives the $i > 1$ components of $\Theta_\tau \Omega_\mu \Theta_\tau'$ to zero for large τ. In the following section, we propose an alternative identification scheme which exploits this feature at a long but finite-horizon.

2.2 Finite-Order Long-Run Identification

As in Galí (1999), we aim at isolating technology shocks by their effect on productivity at horizons longer than business cycles. However, we differ from conventional long-run identification by relaxing the requirement that labor productivity has a unit root or that its unit root be fully characterized by the technology process. Instead, we identify the technology shock as belonging to the set of rotations that obtains the maximum forecast-error variance share in productivity at long horizons. As we will show, this imposes a type of long-horizon restriction that we implement via methods first introduced in Faust (1998). Appendix 1 contains a more detailed exposition of the solution algorithm.

We choose a large, finite k such that the technology shock yields the maximum forecast error variance share of all possible shocks.[6] Under this assumption, we identify the technology shock as the α^* (an $n \times 1$ vector) that solves the following quadratic programming problem:

$$\max_{\alpha} \frac{e_i' \left[\sum_{\tau=0}^{k} \Theta_\tau \alpha \alpha' \Theta_\tau'\right] e_i}{e_i' \left[\sum_{\tau=0}^{k} \Theta_\tau \Omega_\mu \Theta_\tau'\right] e_i}. \tag{7}$$

subject to $\alpha'\alpha = 1$.[7]

Allowing for parameter uncertainty emphasizes several important differences between the two approaches. First, as demonstrated in EGG and CKM, LSVARs have been shown to perform poorly in simulated data from standard RBC models when the sample size is set simimlar to that of postwar U.S. data. Second, there may be cause for relaxing the assumption that there is a unit root in productivity. In particular, differencing productivity in the VAR on the basis of unit root pretests may result in misspecification error because of the low power of these tests [Sims (1989)]. Finally, Uhlig (2003), Fisher (2003), and others argue that factors other than technology can affect the long-run variance of productivity (e.g., capital tax shocks). By maximizing the forecast error variance in productivity due to technology at a finite horizon, our approach implicitly accounts for these considerations, while not precluding a unit root in productivity.

While the MFEV approach has some advantages in small samples, the fact that the identification is data dependent may introduce an additional source of error. In small samples, regardless of whether or not the unit root assumption holds in the population, it is possible to attribute too much of the forecast-error variance in productivity to technology due to errors in estimating Θ_τ. Given this trade-off, whether the MFEV identification yields a net advantage in small samples must be determined. In the next section, we measure the net effect of employing the MFEV identification by comparing the small-sample performance of the LSVAR and MFEV identifications against a

[6] Our identification is similar in flavor to that proposed in Uhlig (2003) in that we also focus on the conditional variance in productivity at a finite (in Uhlig's case, medium term) forecast horizon. The primary difference is that we allow the data to determine the value of the FEV share attributable to technology. Uhlig fixes the FEV share to a value chosen by a calibrated model.

[7] In appendix 2, we show that, in the absence of parameter uncertainty, there exists a finite $k > \overline{k}$ for which $\alpha^* = A_0^{-1} e_j$ under the LSVAR restriction embodied in assumption A.1. Thus, in principle, our approach has the capacity to obtain the same solution as LSVAR when assumption A.1 holds.

known data-generating process.

3 Monte Carlo Experiments

Recent studies – e.g., CKM and EGG – employ Monte Carlo methods to determine the appropriateness of LSVARs in identifying technology shocks in small samples. These authors calibrate an RBC model in which (4) holds to obtain theoretical impulse responses to a technology shock and to generate repeated small samples of simulated data. From these data, they compute small-sample distributions of estimated impulse responses obtained under the LSVAR identification. Thus, if the LSVAR is indeed an appropriate tool for identifying technology shocks, it should produce responses that closely mimic the theoretical impulse responses when applied to the model-generated data. Otherwise, the validity of conclusions drawn when using LSVARs to study technology shocks come into question.[8]

This section performs a similar exercise for the MFEV approach using the neoclassical growth model presented in Francis and Ramey (forthcoming), that corresponds to the fixed capital utilization simulation in EGG. We repeat the exercise for the LSVAR approach to compare its performance to the MFEV approach with a horizon exogenously taken to be 10 years (i.e., the technology shock is chosen to be that which maximizes the forecast-error variance share at a horizon of 10 years). We compare both methods on several grounds. First, we check the robustness of both identifications to relaxation of the assumption of a unit root in technology. This latter specification may be especially important in the face of the low power of standard unit root tests in finite samples. Second, we compare both methods under different assumptions on the persistence of non-technology shocks. Persistent non-technology components in productivity – e.g., persistent capital taxes – may contaminate the identified technology process if not properly isolated. Our analyses compare the ability of the LSVAR and MFEV to isolate technology from any such persistent non-technology component(s). Our model follows.[9]

[8]A comparison of the theoretical impulse responses and those obtained from the LSVAR using model-generated data can reveal a number of qualitative differences. Cooley and Dwyer (1998) and CKM find that LSVARs can reverse the signs of model-generated impulse responses. Based on this finding, they conclude that LSVARs introduce sufficient bias that the estimated impulse responses cannot be considered reliable. However, EGG find that Galí-type restrictions do not reverse the qualitative responses but tend bias their magnitude.

[9]As in the other Monte Carlo work of this nature mentioned above, it is important to caution that conclusions drawn from this approach cannot be generalized beyond the underlying model. That is, our method may be able to replicate the *true* impulse responses generated by this particular model but fail to do so with another model.

3.1 Our Baseline Theoretical Model

For our baseline model, households choose consumption, C_t, labor, N_t, and investment, I_t, to maximize the expected present-discounted value of utility:

$$U(C_t, N_t) = \sum_{t=1}^{\infty} \beta^{t-1} \left[\ln(C_t) + \Phi_t \ln(1 - N_t)\right],$$

subject to a standard budget constraint:

$$C_t + I_t = (1 - \varsigma_{nt})W_t N_t + (1 - \varsigma_{kt})r_t K_t + \delta \varsigma_{kt} K_t - \Psi_t,$$

The equation characterizing the evolution of capital, K_t,

$$K_t = (1 - \delta)K_{t-1} + I_t,$$

and an economy-wide resource constraint:

$$C_t + I_t + G_t \leq Y_t.$$

and a government spending constraint:

$$G_t = \varsigma_{nt} W_t N_t + \varsigma_{kt}(r_t - \delta)K_{t-1} + \Psi_t.$$

where r_t is the pre-tax return on capital, W_t is the real wage rate, δ_t is the depreciation rate, β is the discount factor, Ψ_t is a lump-sum tax, τ_{it} is the tax on labor, and ς_{kt} is the tax on capital income. Consumers own the capital and rent it to firms. The government runs a balances its budget each period and finances its spending through a combination of lump-sum taxes and distortionary labor and capital income taxes. Tax growth rates on labor income and capital are stochastically determined by $\tau_{it} = \rho_i \tau_{it-1} + \sigma_{\tau_i} \varepsilon_{\tau_i}$, $i = k, n$ (where $\tau_{it} = \ln(\varsigma_{it}) - \ln(\overline{\varsigma})$, and $\overline{\varsigma}$ are the steady state values). The preference growth process, ϕ_t, and the growth rate for government purchases, g_t, have similar first-order autoregressive processes. Finally, output is determined by a Cobb-Douglas production technology:

$$Y_t = (Z_t N_t)^{\alpha} K_{t-1}^{1-\alpha},$$

where Z_t is an exogenous process for labor-augmenting technological innovation, $z_t = \rho_z z_{t-1} + \sigma_z \varepsilon_{z_t}$ is the log of technology, and $\varepsilon_z \backsim i.i.d.N\left(0, \sigma_z^2\right)$.

We can then generate impulse responses and simulated data for a variety of parameterizations.[10,11] Table 1 presents the sets of parameter values used to simulate the model. We experiment with several values of the shocks' persistence in order to determine whether the long-run restriction and/or the MFEV approaches come close to the theoretical responses under different parameterizations.[12]

3.2 Results

Similar to CKM and EGG, we estimate a four-variable VAR of productivity, hours, the consumption-output ratio, and the investment-output ratio. The VAR reduced-form parameters are estimated via maximum likelihood in the following Monte Carlo exercises and in the data section below.[13] Productivity enters the VAR in first differences for the LSVAR but enters in levels for the MFEV approach.[14] The benchmark case has the AR(1) coefficient of technology, ρ_z, set to one with all other stochastic processes having AR(1) coefficients of 0.6. Subsequent specifications test near unit root technology processes and more persistent non-technology shocks. All other parameter values are held constant across specifications.

[10] The model is solved by first eliminating nonstationarities arising from technology by dividing Y_t, K_{t-1}, I_t, C_t, G_t, W_t, and Ψ_t by Z_t. Next, the necessary first-order and steady-state conditions are computed based on selected parameter values. We then log-linearize the model around the steady-state growth paths and solve for the recursive equilibrium law of motion using the method of undetermined coefficients. A more detailed explanation of this procedure for solving dynamic stochastic models can be found in Uhlig (1999).

[11] The model produces data that are a deviation around the steady-state growth path. To facilitate comparison with existing empirical work, we need to reverse this transformation. This avoids overdifferencing productivity using the transformed data. We also restrict the simulated data to be of length 174 sample points in order to match the typical length of postwar U.S. quarterly data; we make 5000 draws of sample size of 174.

[12] We ensure that VAR representation exists under each parameterization. Writing the model in its VARMA form, we can verify that the MA portion is invertible. Appendix 3 presents the derivation of the VARMA representation. Numerical calculations confirm that each parameterization has a VAR representation.

[13] For the LSVAR, we assume 80 quarters as our benchmark. For the MFEV approach, we maximize the FEV over shorter horizons – usually 40 quarters. Reducing the horizon in the MFEV extimation avoids estimating coefficients over long lags.

[14] We also experimented with entering productivity in differences and then backing out the levels before maximizing the FEV share. This specification, which is not robust to near-unit behavior in productivity in small or large samples, resulted in larger median biases for the responses compared with the cases presented here.

3.2.1 Impulse Responses

Figures 1 to 4 present the impulse responses to a one-percent shock to technology for various model parameterizations. The thick solid line depicts the theoretical impulse responses, while the dotted and thin solid lines show the median responses from the LSVAR and MFEV approach, respectively. We present the accompanying 68% probability intervals from the simulated small-sample distributions for both empirical approaches. The model generated responses reveal that, in response to a positive technology shock, labor productivity rises and converges to a higher steady state, hours rise on impact and gradually return to zero, the consumption-output ratio falls on impact and also slowly returns to zero, and the investment-output ratio rises before eventually returning to its original steady state.

Figure 1 depicts our benchmark case, in which technology has a unit root and the non-technology shocks have first-order coefficients of 0.6. At first glance, the qualitative results for the two approaches are encouraging although they display some obvious biases. The LSVAR responses corroborate EGG's findings that the LSVAR biases the median responses but preserves their qualitative nature. The MFEV responses, while still biased, perform considerably better. Although the theoretical impulse response for productivity is near the upper tail of the 68% probability interval for both methods, the median productivity response of the MFEV demonstrates less bias and the error bands associated with the MFEV are much narrower. The MFEV bias for the response of the other variables is also generally smaller for the first 4 quarters and the MFEV intervals are somewhat narrower.

Figure 2 shows the response in the case in which technology has a unit root and all other stochastic processes have AR(1) coefficients of 0.98. The relative performance of the two approaches is similar to Figure 1 with respect to the productivity response. However, for the non-productivity variables, the LSVAR error bands contain zero as an impact response while the error bands for the MFEV are bounded away from zero in the same direction as the data generating process. This suggests that, in small samples, the MFEV is better able to identify the technology shock than the LSVAR approach regardless of the persistence of the other shocks.

Now consider the case in which the technology shock is persistent yet stationary. Figures 3 and 4 depict the cases when the AR(1) coefficient on technology is 0.98 and non-technology shocks have first-order coefficients of 0.6 and 0.98, respectively. Biases caused by the LSVAR may now be due to both small sample error and misspecification resulting from differencing (stationary) productivity, and in the case of Figure 4, the presence of other persistent shocks. Obvious from these graphs is that, regardless of the persistence of the non-technology components, the MFEV approach still outperforms the long-run restriction approach when identifying a persistent yet stationary technology shock. When the non-technology components are less persistent (Figure 3), the median responses of the MFEV approach always lies closer to the theoretical responses. Indeed, the LSVAR error bands do not contain the model impulse responses for the first few periods, whereas the MFEV do. When the non-technology components are even more persistent (Figure 4), the relative improvement of the MFEV is large in terms of the width of the confidence intervals. In both of these cases, as in Figure 2 above, the LSVAR error bands contain zero while the MFEV bands do not. This suggests that the LSVAR has more difficulty differentiating the technology from the non-technology shocks.

3.2.2 Correlation of Shocks

To further differentiate the two empirical approaches, we present the correlations between the technology shocks from the data generating process and their estimates from the LSVAR and the MFEV identifications. Table 2 presents the median and the 16th and 84th quantiles of the correlations taken from the simulations.

As expected, the LSVAR identification performs best when technology is a unit root. Under the specifications with $\rho_z = 1$, the correlations between the technology shocks from the model and the LSVAR approach are 0.79 and 0.64, respectively, versus values of about 0.60 when technology is a near unit root ($\rho_z = 0.98$). However in every case, the technology shocks identified by the MFEV approach are much more highly correlated with the realized shocks from the model. When the model parameterization accords most closely with the key LSVAR assumptions –technology follows a unit root and the non-technology shocks are not important at long horizons– the LSVAR performs at its best, but the MFEV still performs better. When the technology shock coefficient is 0.98 is no longer a unit root, the LSVAR correlations decline significantly (to about 0.6) whereas the MFEV correlations increase slightly. Indeed, when the technology shock is a near unit root and other shocks are persistent, the distribution for the MFEV is far to the right of and has little overlap with the LSVAR distribution.

4 Max FEV Share Identification in the Data

Having evaluated the performance of our identification scheme through Monte Carlo experiments, we turn to the data. We estimate a four-variable, four-lag VAR with and without the Sims-Zha (1998) prior.[15] The data are quarterly series for private business productivity, private business hours, real consumption as a share of output, and real investment as a share of output. All variables enter as log levels. Raw data are taken from the BEA and BLS. The error bands are computed using methods described in Sims and Zha (1999).

Figure 5 shows the responses with 68% error bands in the case of no prior (the thin solid and dashed lines) and Figure 6 shows the same model results when estimated with the Sims-Zha prior. Interestingly, except for hours, the responses are in the same direction as those from the theoretically generated responses in the previous section. In response to a positive technology shock, the consumption share of output decreases and the investment share increases; however, labor hours fall for the first few quarters and then eventually rise above zero.

As some variation exists in the data, we estimate versions of this model including nonstandard constructions for consumption and investment as well as hours and productivity measures that are adjusted for demographically-persistent components (see Francis and Ramey 2004b).[16] The variable responses to a technology shock were qualitatively similar across these models. In the results that follow, the benchmark model shown in Figures 5 and 6 is labeled model A and models C-D incorporate various combinations of the different series.[17]

The finding that hours respond negatively to a positive technology shock corroborates Galí's original finding, however one might reasonably wonder about the robustness of this conclusion.

[15] The estimates based on the informative prior account for cointegration and non-stationarity in the underlying series and a belief about the decay of lag parameters. We show below that our results are robust to inclusion or exclusion of the prior, although the conclusions are, in some cases, statistically more distinct when the prior is included.

[16] Models A and B use the standard real consumption and investment series. Models C and D employ alternative constructions for these series, where consumption is composed of nondurables, services, and government spending and investment is composed of private investment plus durables. In addition, models A and C use a standard measure of private business productivity and hours, while models B and D use hours and productivity measures that are adjusted for demographically-persistent components. All findings in this section are invariant to correcting productivity and hours for demographic persistence and to the chosen measures of consumption and investment unless otherwise noted.

[17] In future versions of the paper, we intend to incorporate results based on models that include only hours and productivity, as well as models which include additional variables such as an interest rate and/or a capital tax rate.

It is not hard to imagine, that there might be other plausible modifications to the identifying assumption that yield a different qualitative prediction for hours. We can imagine, for example, that a small shift in the specification of long-run productivity might yield a positive hours response by allowing for more accommodative monetary policy or greater influence of non-technology factors. Taking all such possibilities into account, a more complete robustness test asks whether *there exists a reasonable specification of technology shocks that yields a positive response in hours?*

A salient advantage of the MFEV approach is that it provides a means to address this larger question. Specifically, we reestimate the MFEV model conditional on an additional restriction that hours respond positively on impact to a positive technology shock and then examine whether this has a discernible effect on the forecast-error variance share attributable to technology.[18]

The thick solid lines in Figures 5 and 6 show the point estimates of the impulse responses when the models are estimated with an additional restriction that hours respond positively on impact to a positive technology shock. Examination of the productivity responses shows that they are indeed similar to the unrestricted cases. Yet the responses of the other variables have changed considerably. The response of hours in the more restricted model estimated without a prior lies near the upper end of the 68% interval from the less restricted model, while the hours response in Figure 6 lies entirely above the less restricted 68% interval. The response of the consumption and investment shares is also magnified when hours are restricted to be positive.

Tables 3 and 4 show the MFEV shares for productivity in models A-D estimated with and without a prior as well as the corresponding 68% error bands. The fourth and fifth columns in these tables present MFEVs from the same models estimated with an additional restriction that hours responds positively on impact. In every case, the maximum attainable forecast-error variance share in labor productivity declines when we require that hours respond positively to the technology shock. Moreover, there is little overlap in the probability intervals for the MFEV in the two cases. This shows that a positive hours response is attainable, but only if we are willing to relax the importance of technology shocks at the ten year horizon, implying a larger role for non-technology shocks.[19] A reasonable interpretation of this result is that it implies that the negative

[18] Appendix 1 details how marginal sign restrictions are incorporated into the MFEV identification approach. Note that an additional restriction on hours is not an overidentifying restriction that would lend itself to a likelihood ratio test. The identifying assumption on productivity is sufficent to identify technology but the system as a whole is underidentified with or without the additional sign restriction.

[19] Note that it does not necessarily follow that there are in fact other influences on long-run productivity. Odds

hours prediction in LSVAR models depends decisively the assumption that non-technology shocks have no such role for non-productivity shocks.[20]

At the same time, the differences in the MFEV shares are not large. The additional restriction lowers MFEV share by as little as 6 percent and by no more than 25 percent and technology remains by far the dominant influence in all of the cases. Thus in our view, it makes sense to think of these cases as part of a general class of models that require a dominant (possibly exclusive) role for technology in labor productivity at a very long finite, or infinite, horizon Seen from this perspective, our results indicate that long-run restrictions as a class appear to contain limited information about short-run movements in hours. While similar, in an economic sense, in their specification of technology, individually these models have potentially very different implications for the effect of technology shocks on labor hours.

4.1 MFEV versus LSVAR

Figures 7 (no prior) and 8 (Sims-Zha prior) show the empirical responses to a technology shock identified by the LSVAR (dotted) and MFEV (solid) approaches in model A with their associated 68% error bands. The two approaches clearly obtain important differences. Most obviously, the error bands associated with the MFEV estimates are always much narrower. Indeed, in Figure 8 the MFEV error bands are nearly always fully contained in the LSVAR error bands. Further, the short-run responses in the non-productivity variables are much smaller in the MFEV estimates for the same sized initial technology shock.

A closer examination of the response of hours in Figures 7 and 8 yields a final observation that touches on the controversy surrounding the specification of that series. The LSVAR estimates in Figure 7 corroborate the finding in CEV (2004) that hours respond positively to a technology shock when the series enters the VAR in levels.[21] However, when we estimate the model with the Sims-Zha prior as in Figure 8, the sign reverses. This suggests that the low frequency components of hours are relevant in determining the sign on the hours response in the LSVAR estimates in Figure 7. When we perform the same exercise on the demographically-detrended hours series in model B,

ratios for the restricted and unrestricted models were indistinguishable, preventing us from drawing such a conclusion.

[20] This interpretation is reasonable since there is likely little difference of economic significance between ten years and an infinite long-run horizon.

[21] Recall that hours enters in log levels in all models presented in this paper whereas they enter in differences in the LSVARs presented in Galí (1999) and Francis and Ramey (forthcoming).

we find that hours respond negatively when estimated with or without a prior. In contrast, hours respond negatively under the MFEV approach whether or not the estimation includes a prior and whether or not the data is demographically adjusted.[22]

5 Conclusion

We propose an alternative method for identifying technology shocks that is robust to relaxing key assumptions about the data-generating process. While maintaining the spirit of long-run restrictions on labor productivity, our proposed method identifies the technology shock as that which yields the maximum forecast-error variance share in productivity at some predetermined, yet finite, horizon.

Applied to artificial small samples generated from an off-the-shelf neoclassical growth model, our identification technique more closely replicates the model generated impulse responses. In addition, the identified impulse responses provide more precise coverage than the standard long-run restrictions first proposed by Galí (1999). We also find that the technology shocks implied by our MFEV methodology are more highly correlated with the shocks underlying the data processes than the shocks identified by the long-run approach. These results evince a clear improvement over LSVAR estimates in small samples. This improvement is even greater in the presence of highly persistent but stationary technology shocks or confounding persistent non-technology shocks.

When taken to actual data, the MFEV model predicts a negative short-run response in hours, confirming the original LSVAR hypothesis. However our robustness analysis finds that a positive hours response is attainable if we allow for an increased (albeit modest) role for non-technology shocks. Although we are unable to measure which model has higher probability, our results suggest that the rejection of the RBC framework on the basis of the qualitative response in hours depends critically on whether one is willing to assume that technology has exclusive influence on long run productivity.

Viewing our model and the infinite horizon models as a class, however, our results can also be interpreted negatively as a demonstration of the limitations of long run restrictions in predicting short-run movements in hours. It takes only a very modest, and likely empirically reasonable,

[22] Results available upon request.

adjustment in the long run assumption regarding the importance of non-technology factors to obtain very different prediction for the sign on hours. With this lesson in mind, we nonetheless believe that long-run restrictions add relevant information structure to the data. Indeed our work suggests that augmenting long-run restriction models with additional structural information is a promising direction for future research.

Table 1		
Parameter Values Used in Model Simulation		
Parameter	**Description**	**Value**
α	capital share	0.36
δ	quarterly depreciation rate	0.02
β	discount factor	1/1.03
ρ_z	autocorrelation of technology shock	0.98 & 1
ρ_k	autocorrelation of capital tax shock	0.6 & 0.98
ρ_n	autocorrelation of labor tax shock	0.6 & 0.98
ρ_g	autocorrelation of government spending shock	0.6 & 0.98
ρ_Φ	autocorrelation of preference shock	0.6 & 0.98
$\overline{g}/\overline{y}$	steady state ratio of government to output	0.03
$\overline{n}$	steady state labor	1/3
$\overline{\tau}_k$	steady state capital tax rate	0.38
$\overline{\tau}_n$	steady state labor tax rate	0.22

Table 2				
Percentiles of Posterior for Correlation of Structural Shocks				
		$16th$ percentile	median	$84th$ percentile
$\rho_z = 1; \rho_{non-z} = 0.6$	LSVAR	0.29057	0.79503	0.91648
	MFEV	0.84106	0.90234	0.93721
$\rho_z = 1; \rho_{non-z} = 0.98$	LSVAR	0.32088	0.63779	0.84015
	MFEV	0.67098	0.83063	0.91003
$\rho_z = 0.98; \rho_{non-z} = 0.0.98$	LSVAR	0.30701	0.60688	0.82965
	MFEV	0.68372	0.84119	0.91851
$\rho_z = 0.98; \rho_{non-z} = 0.6$	LSVAR	0.22422	0.59424	0.86757
	MFEV	0.84669	0.90581	0.94094

Table 3				
MFEV_{10}(prod) Share (estimated without SZ prior)				
	Unrestricted		$\text{Hours}_0 \geq 0$	
Model	Pt. Est.	68% interval	Pt. Est.	68% interval
A	.9512	(.9506, .9929)	.8757	(.8452, .9674)
B*	.9343	(.9448, .9825)	.8572	(.8194, .9628)
$\text{C}^{\top}$	.8243	(.8876, .9669)	.7751	(.8067, .9359)
$\text{D}^{*\top}$	.9484	(.9635, .9922)	.7373	(.7963, .9482)

* Demographically adjusted productivity and hours

$\top$ Durable consumption excluded from consumption and included in investment;government consumption included in consumption

Table 4				
MFEV$_{10}$(prod) Share (estimated with SZ prior)				
	Unrestricted		Hours$_0 \geq 0$	
Model	Pt. Est.	68% interval	Pt. Est.	68% interval
A	.9957	(.9969, .9997)	.9086	(.8933, .9875)
B*	.9958	(.9948, .9994)	.9318	(.8980, .9916)
C$^\top$	.9944	(.9972, .9996)	.9262	(.9069, .9931)
D*$^\top$	.9962	(.9947, .9993)	.9508	(.9099, .9941)

* Demographically adjusted productivity and hours

$\top$ Durable consumption excluded from consumption and included in investment;government consumption included in consumption

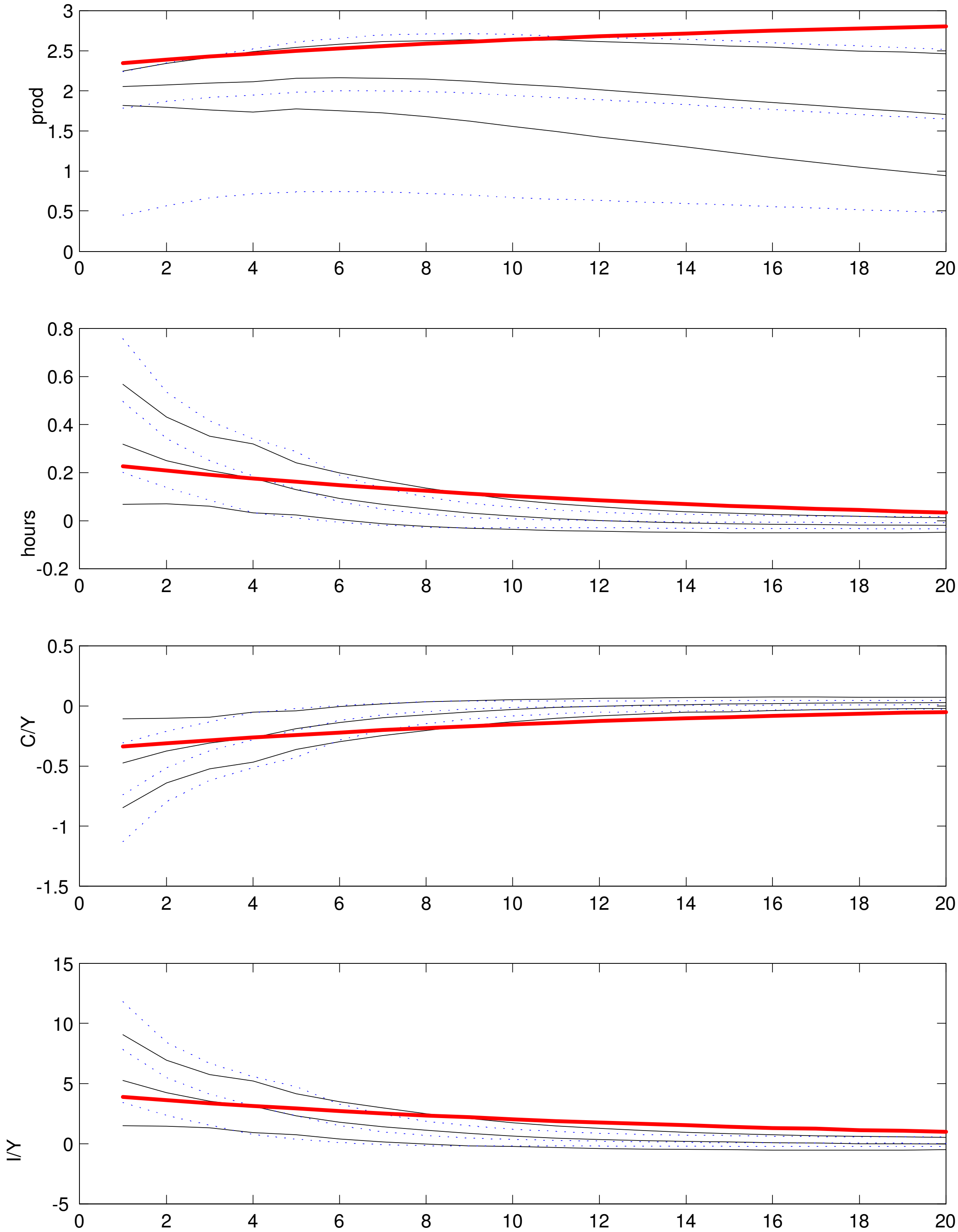

Figure 1: Impulse Responses to a Technology Shock with $\rho_z = 1.0$ and non-technology $\rho = 0.6$ in DGP (thick solid) vs. LSVAR (dot) and MFEV(thin solid)

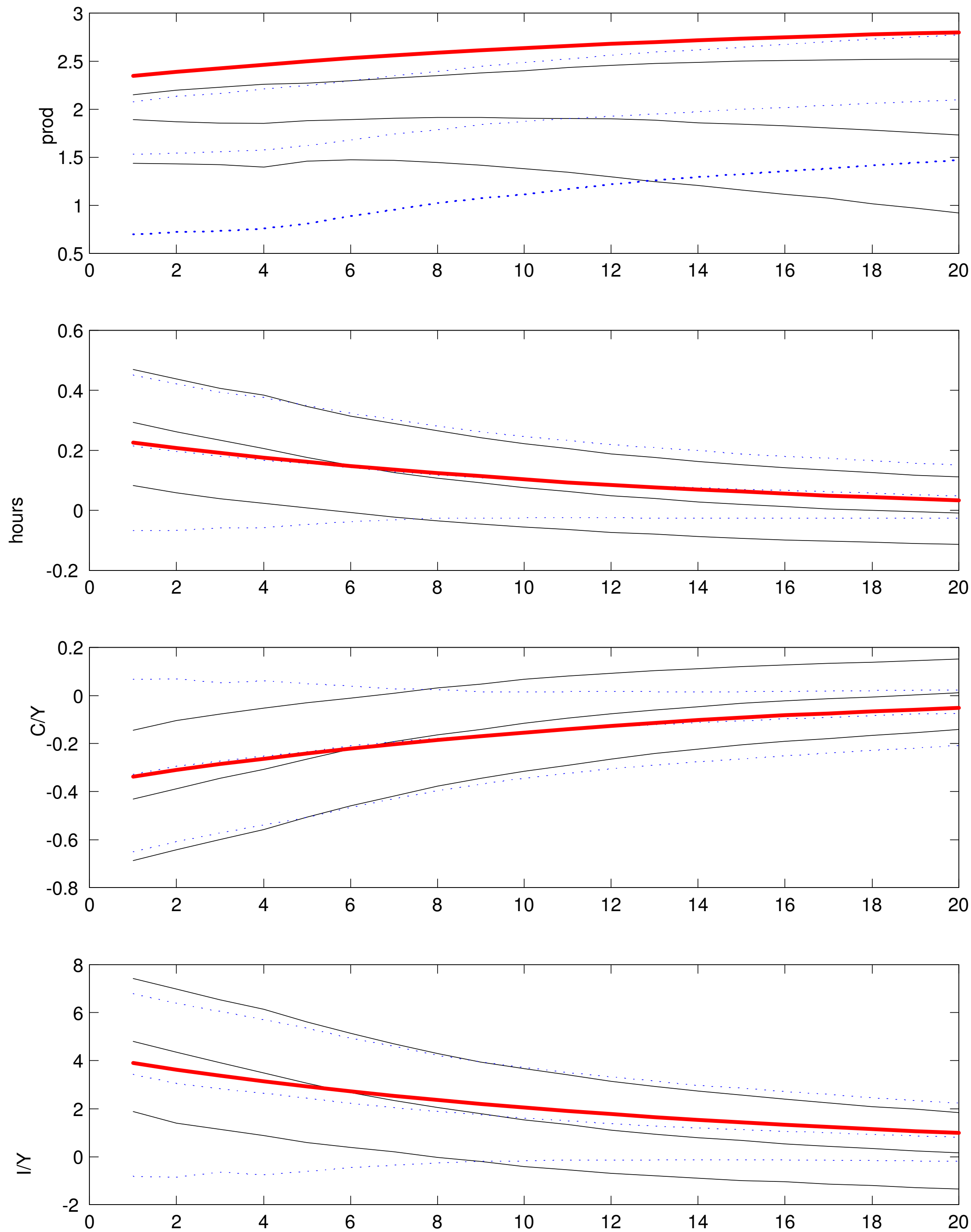

Figure 2: Impulse Responses to a Technology Shock with $\rho_z = 1.0$ and non-technology $\rho = 0.98$ in the DGP (thick solid) vs. LSVAR (dot) and MFEV(thin solid)

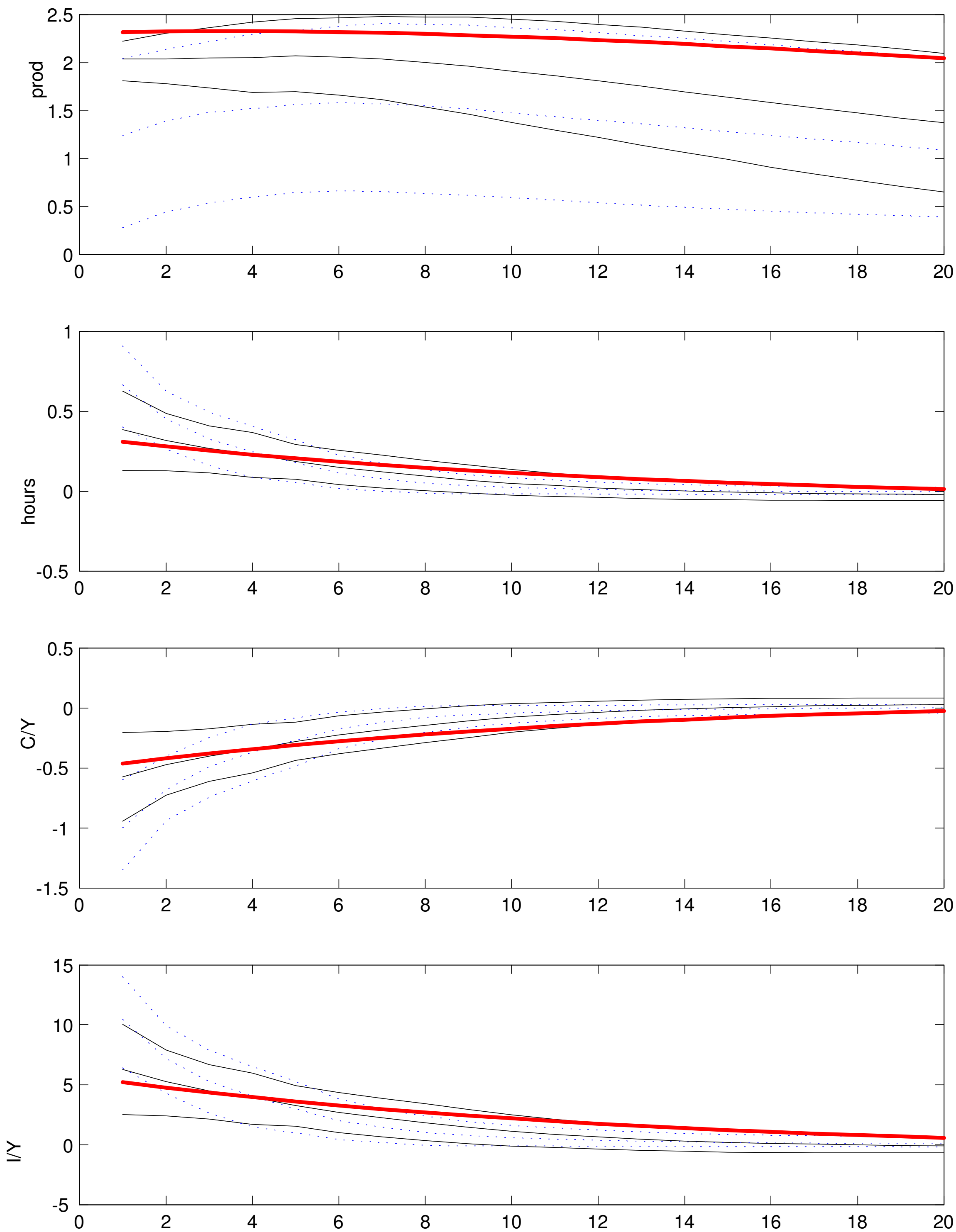

Figure 3: Impulse Responses to a Technology Shock with $\rho_z = 0.98$ and non-technology $\rho = 0.6$

DGP (thick solid) vs. LSVAR (dot) and MFEV(thin solid)

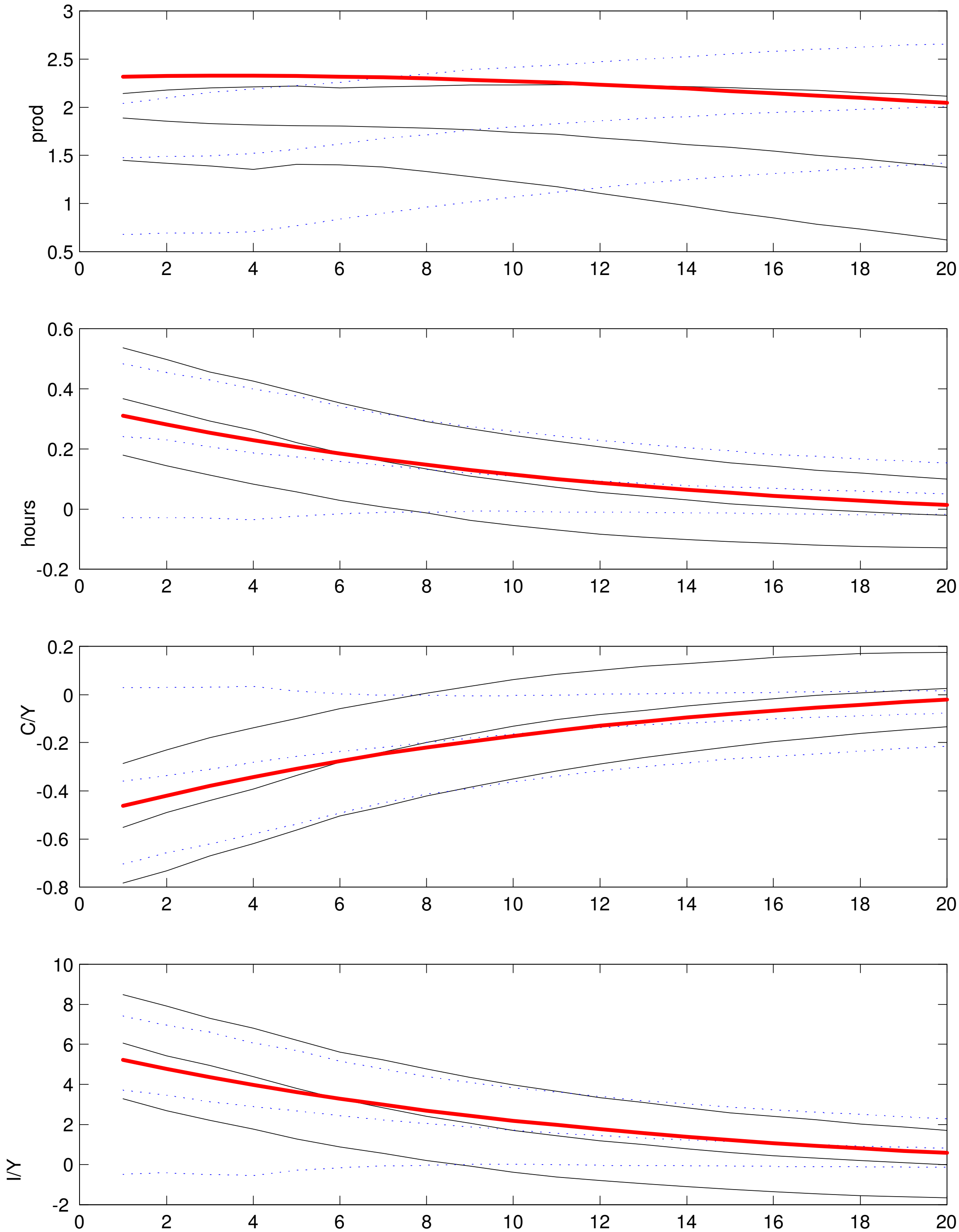

Figure 4: Impulse Responses to a Technology Shock with $\rho_z = 0.98$ and non-technology $\rho = 0.98$

DGP (thick solid) vs. LSVAR (dot) and MFEV(thin solid)

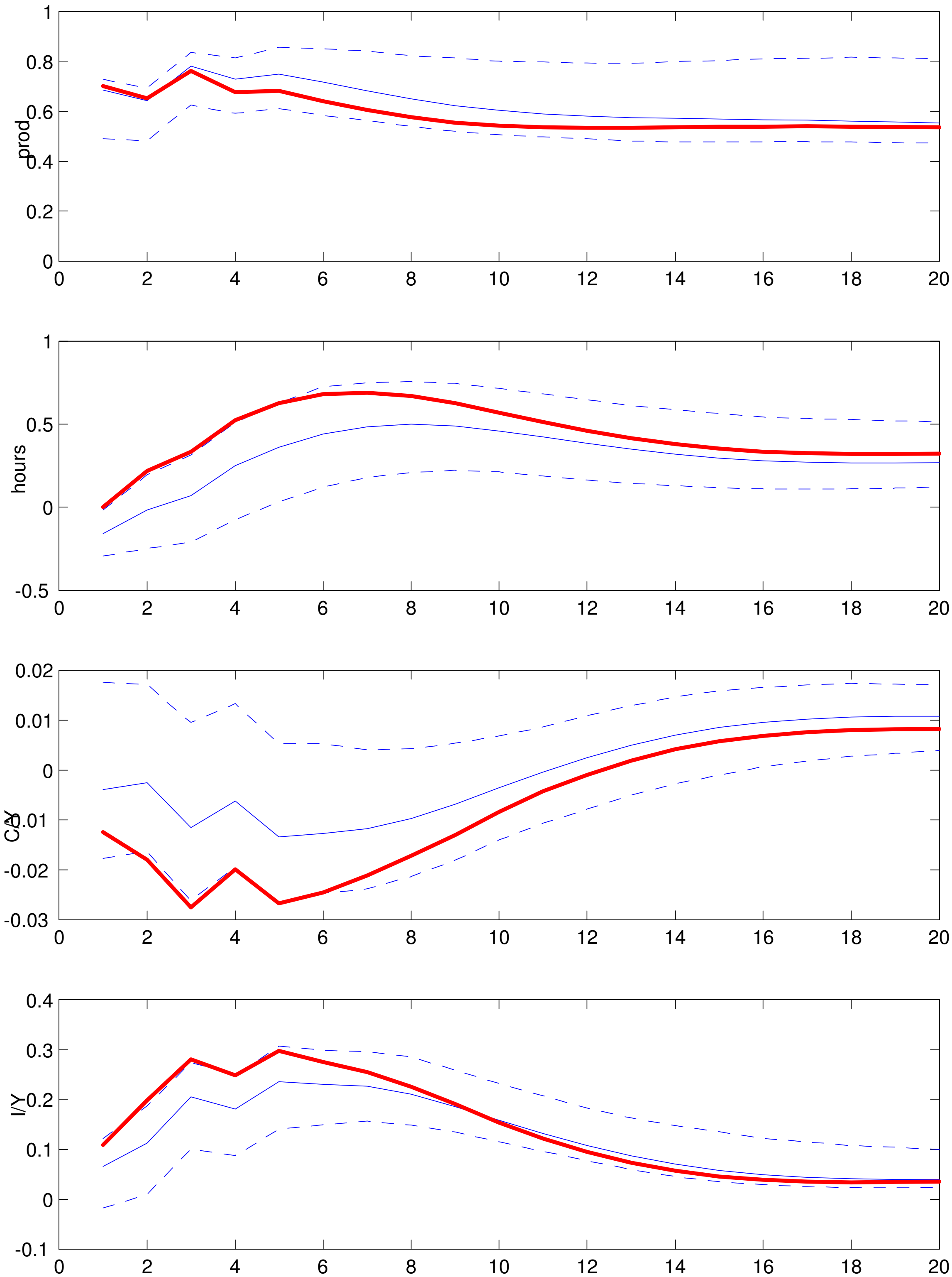

Figure 5: Impulse Responses to a Technology Shock in MFEV estimated without prior: Unretricted (thin solid and dash) vs. with hours positive (thick solid)

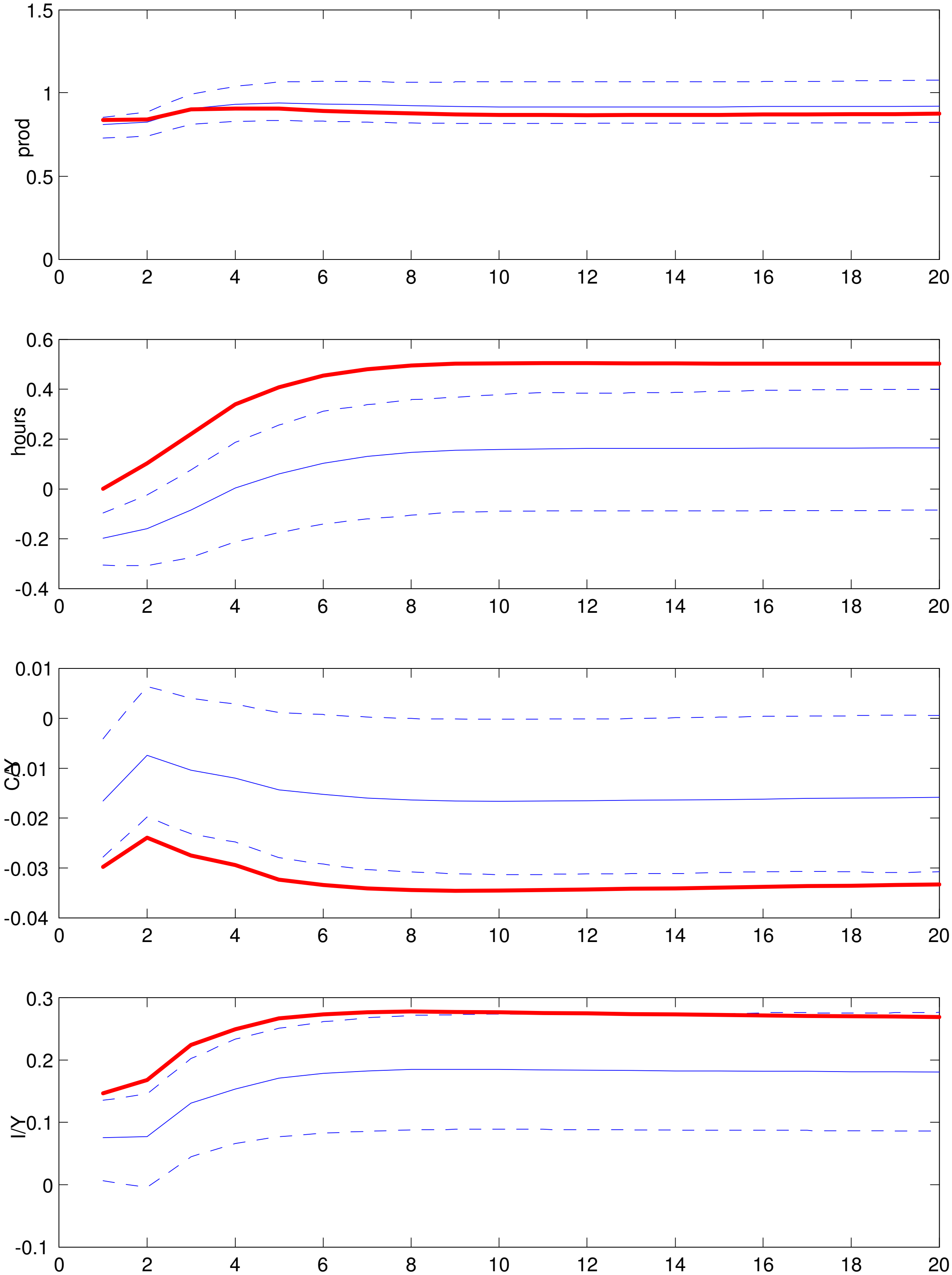

Figure 6: Impulse Responses to a Technology Shock in MFEV estimated with Sims Zha prior: Unrestricted (thin solid and dash) vs. with hours positive (thick solid)

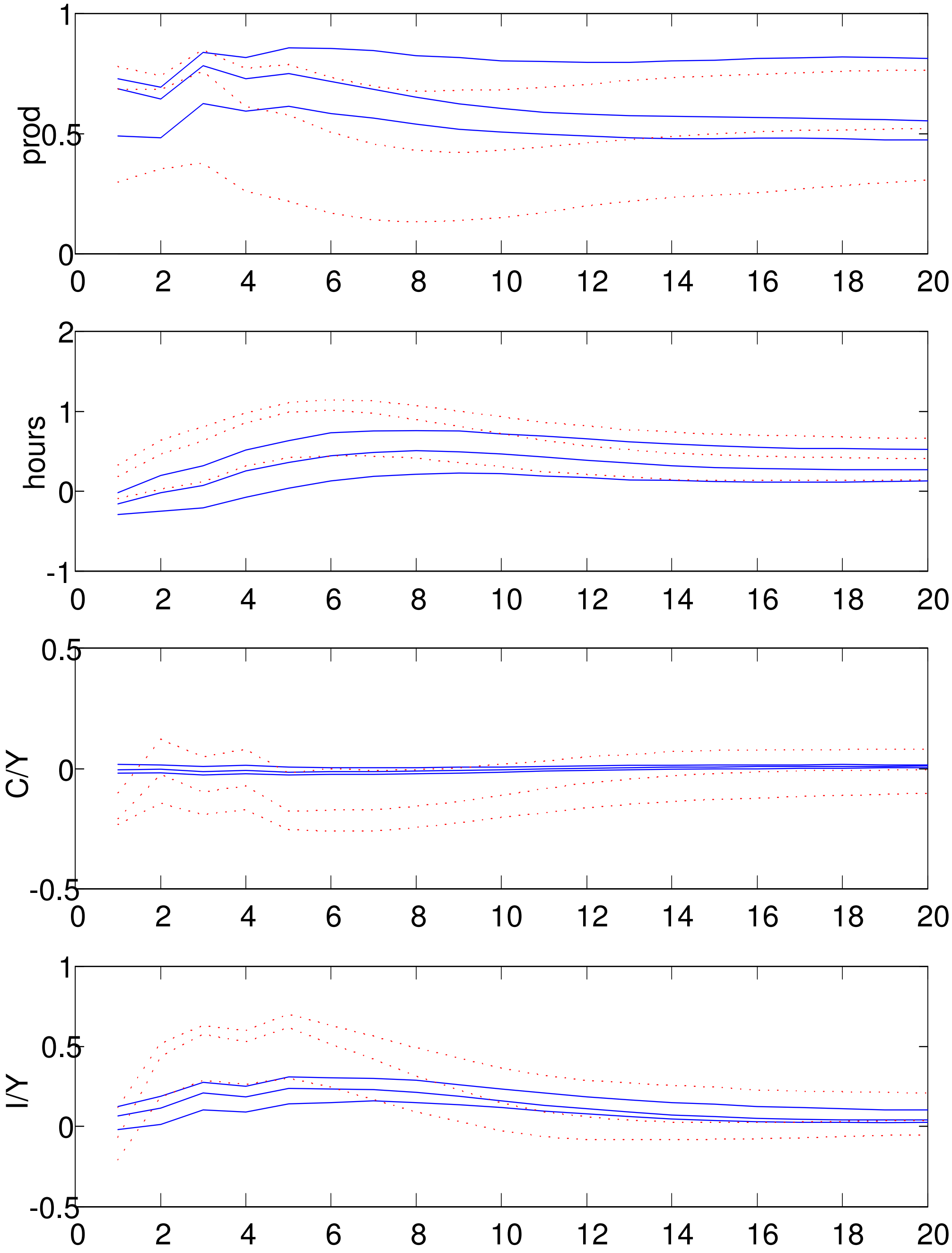

Figure 7: Impulse Responses to a Technology Shock Estimated (Without Prior) via: MFEV (solid) and LSVAR (dotted)

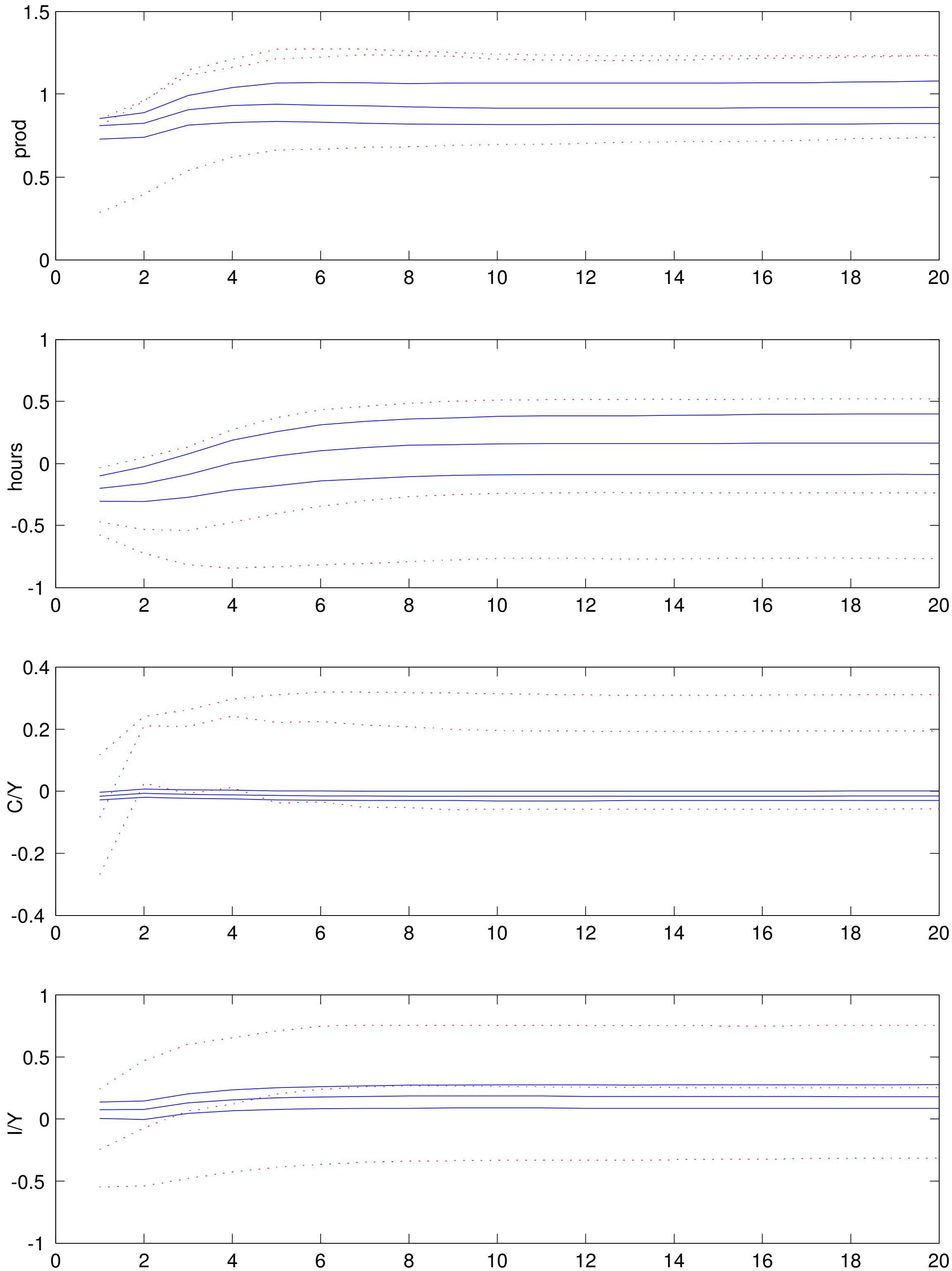

Figure 8: Impulse Responses to a Technology Shock estimated with the Sims Zha prior via: MFEV (solid) and LSVAR (dotted)

6 Appendix 1: The Max Forecast-Error Variance Identification Algorithm

This appendix formalizes the search algorithm employed by our MFEV identification, based on the methodology first introduced by Faust (1998). We begin by forming a generic moving-average representation of the estimated VAR using a Cholesky decomposition of the one-step-ahead forecast errors, $H = chol(\Omega)$:

$$y_t = C(L)HH^{-1}\varepsilon_t. \tag{8}$$

Next, consider the space of observationally equivalent representations of this generic form, which can be expressed as linear rotations of (8), each formed according to an orthonormal matrix D:

$$y_t = \widetilde{C(L)}DD'\widetilde{\varepsilon}_t, \tag{9}$$

where now $\widetilde{C(L)} = C(L)H$ and $\widetilde{\varepsilon}_t = H^{-1}\varepsilon_t$. The dynamic response of y_t to the jth shock is denoted $\widetilde{C(L)}\alpha$, where α is the jth column of D. The jth shock in $D'\widetilde{\varepsilon}_t$ is then $\alpha'\widetilde{\varepsilon}_t$. In our previous notation, A_0 is one element of the space of possible Ds. However, in this case, our objective is to identify only one shock (one column of A_0), which we will call α^*.

Following Faust (1998), we identify α^* as the vector associated with the maximum forecast-error variance share for productivity due to the shock $\alpha^{*\prime}\widetilde{\varepsilon}_t$:

$$\alpha^* = \arg\max \alpha' \left[\frac{\sum_{t=0}^{h} \widetilde{C}'_{t,p}\widetilde{C}_{t,p}}{\widehat{\sigma}^2_{p,h}} \right] \alpha, \tag{10}$$

$$s.t.\ \ C^R\alpha \geq 0 \text{ and } \ \alpha'\alpha = 1.$$

Here, $\widetilde{C}_{t,p}(j)$ is the row in $\widetilde{C(L)}$ corresponding to the response of productivity at horizon t and $\widehat{\sigma}^2_{p,h}$ is the full forecast error variance at horizon h. $C^R\alpha \geq 0$ defines a set of linear sign and shape restrictions on the impulse responses of y_t to $\alpha'\widetilde{\varepsilon}_t$. The restriction that α has unit length maintains the normalization of error variance to unity. The quadratic programming problem in (10) is solved by a series of maximum eigenvalue problems over the space defined by $C^R\alpha \geq 0$.[23]

[23] Eliminating cases that do not satisfy the remaining weak inequality restrictions results in a set of $\alpha's$ which satisfy both the linear restrictions and the criterion function optimally within each subspace. Then, the solution is the α associated with the maximum eigenvalue in this set. For more information on the solution algorithm see the

The complete algorithm entails performing the optimization problem in (10) iteratively to find a minimum set of restrictions sufficient to produce impulse responses consistent with our priors about the effects of a technology shock. In this way, if we find that the solution to the unconstrained problem yields an increase in consumption in response to a positive technology shock (that increases labor productivity), we can restrict the domain to the space where these responses are positive by including the following restrictions:

$$C^R\alpha \geq 0 \qquad ;C^R = \left[\widetilde{C}_{0,c}(j)\right] \tag{11}$$

where $\widetilde{C}_{0,c}$ is the row in $C(0)$ corresponding to consumption and the α here is α^{fev} in Section 3.

7 Appendix 2: Comparing Identifications Under A.1

In this appendix, we compare the MFEV identification to the long-run identification at finite horizon $k < \infty$. Suppose that Assumption (A.1) is true. Then, we are interested in determining whether, under parameter certainty, the MFEV methodology identifies the same technology shock as the the long-run restriction. We know that if estimation error is not an issue and the underlying identifying assumption holds, the long-run restrictions identify the technology shock with certainty. Thus, we must show that, in this case, our methodology also identifies the true technology shock.

Essentially, we are arguing that for some large k, Proposition 1 and (7) combine to obtain the unit root solution. Thus, in the absence of parameter uncertainty, there must exists a horizon $\overline{k}$ beyond which the share for the technology exceeds all other shocks and the solution to (7) obtains the true technology shock. For ease of exposition, define the technology shock identified by long-run restrictions in this case as α^{LR}. We summarize this in the following proposition:

Proposition 2 *Suppose Assumption (A.1) and Proposition 1 hold and that $\omega_{i,j}(h)$ is a continuous function. In the absence of parameter uncertainty, there exists $\overline{k}$ such that for all $k > \overline{k}$, $\alpha^* = \alpha^{LR}$.*

Under the assumption that P1 holds, we can always find a k arbitrarily close to ∞ for which $\omega_{11}(k)$ is arbitrarily close to 1. Since $\omega_{11}(k)$ is bounded above by 1, the α^* which yields this FEV

appendix in Faust (1998).

share must also be the α^* that would maximize the FEV share at horizon k. Thus, we can choose k arbitrarily close to ∞ and $\omega_{11}(k)$ continuous so $\alpha^* = \alpha^{LR}$.

An unresolved question surrounds the magnitude $\overline{k}$? In a model without parameter uncertainty, $\overline{k}$ perhaps could, in principle, be found analytically. In an estimated model, $\overline{k}$ might be identified by experimentation, choosing the horizon at which the identified shock's posterior distribution is invariant to increasing $\overline{k}$.[24] In the present draft, we have exogenously chosen $\widehat{k} = 10$ years as a reasonable horizon in that it is longer that business cycle frequencies.

8 Appendix 3: Existence of the VAR Representation

Given the recursive solution

$$x_t = px_{t-1} + Qz_t \tag{12}$$

$$y_t = Wx_t + Sz_t, \tag{13}$$

where x_t is a vector of endogenous state variables (in our case, capital, k, is the lone endogenous state variable), z_t is a vector of exogenous state variables (e.g., technology, A, preference/taste shock, Φ, government growth shock, g, and capital and labor tax shocks, τ_k and τ_n), and y_t is a vector of other endogenous variables (e.g., output, consumption, investment, labor, and the interest rate). The vectors p, Q,W, and S are determined by simulating the model, conditional on the parameter values from Table 1.

Substituting (12) into (13) yields

$$y_t = pWx_{t-2} + WQz_t + Sz_t. \tag{14}$$

Realize that

$$Wx_{t-2} = w_{t-1} - Sz_{t-1} \tag{15}$$

[24] One way to do this in practice is to compute the Kullback-Liebler divergence between the posterior distributions for the identified shocks evaluated at different horizons. The identified shock is chosen to be the one in which the divergence measure reveals a sufficiently small change in the posterior distributions (Owyang 2004).

and substitute (15) into (14). Collecting terms yields:

$$y_t - py_{t-1} = Sz_t + (WQ - pS)z_{t-1}. \tag{16}$$

We can rewrite this in its VARMA form:

$$S^{-1}y_t - (S^{-1}p)y_{t-1} = z_t + S^{-1}(WQ - pS)z_{t-1}, \tag{17}$$

$$D(L)y_t = C(L)z_t.$$

Finally, given the parameterizations from Table 1, we must ensure that the roots of $C(L) = I + [S^{-1}(WQ - pS)]L$ lie outside the unit circle as required for invertibility.

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