Specification and the Technology-Hours Debate: What Can We Learn From Bayesian VARs?

Paul Corrigan[*]
Bank of Canada

Florian Pelgrin
Bank of Canada,
EUREQua, University of Paris I
and OFCE

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Abstract : Many recent papers, following Galì (1999), have found a negative response of employment to a positive technology shock identified as a permanent shock to labor productivity, contradicting the prediction of standard RBC models. In a recent paper, Christiano, Eichenbaum and Vigfusson (2003) get a positive response of employment measured by hours per capita when Galì's assumption of a unit root in hours is relaxed. In this paper, we propose a new specification test to disentangle for the level/first difference models. We calculate posterior probabilities of various specifications of productivity-hours VARs using Bayes factors, measured by the Laplace approximation and by the posterior information criterion suggested by Phillips (1995, 1996) and Phillips and Ploberger (1994). Our results strongly support the results of CEV, namely, a specification of hours in levels rather than differences. However, resulting level VAR implies impulse responses , variance decompositions and conditional correlations with distributions so wide that meaningful inference of the role of technology shocks in business cycles is impossible.

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[*] *Corresponding author:* . E-mail: pcorrigan@bank-banque-canada.ca. We thank Valerie Ramey for providing us her data, and Greg Tkacz for helpful comments......The views expressed here are those of the authors and do not necessarily reflect the views of the Bank of Canada.

1 Introduction

The seminal paper of Kydland and Prescott (1982) and most of the models in the Real Business Cycle literature consistently produce a high positive response of both output and employment (measured by hours worked per capita) to a positive technological shock. In particular, this prediction is robust when the benchmark model allows other shocks for playing a role in the cycle (as for instance, government spending, taxation). However, the high positive correlation between hours and labor productivity seems in contrast to the data, namely, an observed near-zero correlation.

This positive comovement between productivity and labor inputs and the technology shock-based explanation of business cycles have been challenged by the empirical work of Galì (1999). This paper provides evidence that technology shocks are a source of negative correlation between output and hours worked. More specifically, Galì (1999) uses long-run restrictions à la Blanchard-Quah (henceforth, BQ) in a structural VAR model, in which labor productivity and hours are specified in first-differences, and shows that productivity increases and hours fall after a postive technology shock in the U.S., and that the short-run contribution of these shocks to business cycles is rather weak. In subsequent papers, Galì (2004) and Galì and Rabanal (2004) restate these conclusions and therefore question the suitability of RBC models to mimic the behavior of the economy—sticky price models are better suited to reproduce the results of the VAR analysis.

Other papers in the literature have confirmed the findings of Galì (1999).[1] In an earlier contribution, Blanchard, Solow and Wilson (1995) show that an (exogenous) increase in productivity drives the unemployment rate up. Basu, Fernal, and Kimball (2004) attempt to calculate a growth accounting based-measure of technology changes and find that the short-run impact of their new measure on output is small, and its effect on hours worked per capita actually sharply negative. Kiley (1997) and Francis (2001) apply the SVAR framework of Galì (1999) to manufacturing industries and-or sectors and outline a negative correlation between employment and output growth after a positive technology shock for must of the industries and-or sectors considered. Shea (1998) also shows, by using industry level data, that labor input responds in the direction opposite to the movement in total factor productivity. Francis and Ramey (2004a, b) extend the analysis of Galì (1999) in several dimensions and confirm the existing results. Francis and Ramey (2002) provide evidence the Galì's result to be robust after controlling for possible permanent shocks to taxation which could also permanently affect labor productivity. Francis, Owyang and Theodourou (2003) use the sign-restriction methodology proposed by Uhlig (2004), instead of long-run restrictions, and find the opposite result of RBC models. International comparison studies (Galì, 1999, 2004; Francis and Ramey, 2004; Galì and Rabanal, 2004) also show much more evidence for a negative effect on hours worked after a positive technology shock than a positive response of hours series.

Some recent papers, however, questioned the robustness of these empirical findings. Galì's (1999, 2004) papers have been especially subject to at least two lines of criticisms.

On the one hand, the restriction that technology shocks, and these only, have a permanent effect on labor productivity as well as the BQ decomposition have been discussed (Chari, Kehoe and McGrattan, 2004; McGrattam,

[1] The following papers use a stationary transformation of the hours worked series.

2004).[2] Erceg, Guerrieri, and Gust (2004) point that the BQ decomposition might be useful if samples are large enough; however, they find very large small-sample bias when data sets are roughly the length of currently available U.S. time series. In contrast to the previous papers, Uhlig (2003) introduces "medium-run identification" and shows it to be preferable to long-run or short-run identification (when applied to artificial data). Interestingly, Uhlig (2003) finds that a positive technology shock yields an hump-shaped response of total hours; however, the initial response is near-zero. Dedola and Neri (2004) estimate the effects of technology shocks by imposing sign-restrictions of impulse response functions. They show that hours worked are much more likely to increase after a positive technology shock occurs. This result appears to be robust in many dimensions. Peersman and Straub (2003) confirm this result in the euro area. It is to be noted that the positive correlation between labor productivity and hours is robust to the use of a stationary transformation of labor input in Uhlig (2003), Dedola and Neri (2004), and Peersman and Straub (2003).

On the other hand, Christiano, Eichenbaum and Vigfusson (2003b, 2004) argue that the results are very sensitive to the stochastic specification of the hours worked series. Hence, while the estimates in Galì (1999) and much of the studies (finding an inverted hump-shaped response of hours worked) use first-differenced or detrended (log) hours per capita, CEV claim that the only sensible specification for hours was one assuming a reversion of hours (per capita) to a mean, in which case a VAR including first-differenced hours is misspecified. In this respect, CEV find consistent results with the RBC literature when the level of (log) hours worked per capita enters in the structural VAR specification: hours are driven up after a positive technology shock hits the economy. The technology-hours debate thus turns to the stationary transformation of the hours worked series, and its implications for the sources of business fluctuations.

In this paper, we address the question of the specification of the hours in a structural VAR model and we examine the robustness of results in the literature. Our approach differs remarkably from most of previous studies in the sense that we use Bayesian econometrics and we propose a direct test to assess which specification should be used. Specifically, given that it is well-known that standard unit root tests fail to discriminate the *level-first differences* nature of hours, due to low power (see Sims, 1988; Phillips, 1991), and that the stochastic process driven hours affects inference as well as impulse-response functions, the variance decomposition, etc, we rather outline that we can learn from Bayesian specification of structural VAR models. In effect, a Bayesian approach to calculating moments from a structural VAR model seems to have been rarely taken in the context of the technology-hours question in the U.S. (two exceptions being Uhlig (2004) and Dedola and Neri (2004)), much less to picking the "best" specified model of productivity and hours (i.e. using level hours versus differenced hours).

In this respect, we take a Bayesian approach to estimating a bivariate technology-hours VAR by using a version of the Normal-Wishart variant of the Minnesota prior of Litterman (1986), suggested by Kadiyala and Karlson (1997). We then compare the first-differenced and level hours specifications. To do so, we propose a specification test that encompasses the two SVAR models used in the literature. Our method is substantially similar to that of Phillips and Ploberger (1994) and Phillips (1995), who calculated Bayes factors for competing specifications of AR models of the series examined by Nelson and Plosser (1982) and Schotman and Van Dijk (1991). Unlike classical

[2] Standard criticisms of long-run restrictions include Lippi and Reichlin (1993), Cooley and Dwyer (1998), and Faust and Lepper (1997).

model-selection criteria, which are usually functions of the maximum likelihood, Bayes factors are measures of the average likelihood, given a candidate model, the data and a prior distribution on model parameters. When competing models are assumed a priori to be equally likely, the posterior probabilities of each model are proportional to the Bayes factor.[3] Two measures of the Bayes factor are used here to compare models, the first being the Laplace approximation, the second being the Bayesian variant of Phillips' own "posterior information criterion" or PIC, a classical version of which is used to "pick" evolving Bayes models of time series in his 1995 paper and in Phillips and Ploberger (1994). Phillips (1996) applied the Bayesian PIC to specification choice for Bayesian VARs. With the "best" specification in hand, we then use our Bayesian VARs to calculate and examine posterior distribution of moments of interest in examining the effect of technology shocks on hours. Among these are posterior distributions of the Blanchard-Quah decomposed technology shocks and their conditional correlations with productivity growth and hours, as well as more conventional metrics of the effect of technology on hours such as impulse response functions and variance decompositions. Furthermore, we explore the robustness of our results using alternative data set (see Chari, Kehoe and McGrattam, 2004), namely, the CEV data, the Francis-Ramey data and a dataset including the U.S. real GDP and the unemployment rate. Then we experiment larger VAR specifications (using the models of CEV and Galì, Lopez-Salido and Valles (2003)). We also analyze whether our results might be driven by the changes of monetary policy in the United States or the existence of structural breaks (see Dedola and Neri, 2004; Fernald, 2004). Finally, we address the question of how informative our priors are—we re-estimate the VARs using other informative or non-informative priors.

Our results show that a specification of hours in levels rather than differences is rejected in a classical framework, but is strongly supported when we use a reasonable informative or a non-informative prior (Bayesian framework), even one centered on the hypothesis that the difference specification is best. This implies, in turn that the effect of technology on hours is probably positive (and hours are positively correlated with lagged technology shocks). This result strongly supports those of CEV, Delado and Neri (2004) and Uhlig (2004). However, at the same time, the margin of error in the IRFs is too wide to allow a strong conclusion. Therefore, inference from IRFs regarding the response of hours to technology shocks, positive or negative, is fragile to specification and data set used in estimating VARs. The distributions of variance decompositions as well are also far too diffuse to allow a meaningful inference regarding the importance of technology shocks in cycles. Therefore the uncertainty surrounding the impact effect of technology shocks or their contribution support, to some extent, the conclusion of Galì (1999) in the sense that technology might not be the primary source of business fluctuations. Such results are robust to use of VARs with larger data sets (including inflation, interest rates and the investment/output ratio), to sub-sample stability, and the choice of priors.

The rest of this paper is organized as follows. Section 2 describes the method of estimation of the Bayesian VAR models used in this paper, as well as the means of calculating posterior distributions for moments of interest. After briefly describing the data in section 3, we go on in section 4 to note the results of the specification tests for the bivariate VARs, along with discussion of the estimated moments of interest and what they imply about the effect of hours on technology. Section 5 takes a variety of approaches to checking the robustness of our results. Among these are using larger data sets to estimate our VARs allowing us to examine how well technology shocks can explain

[3]For a useful survey of Bayes factors and how to calculate them, see Kass and Raftery (1995).

the business cycle as a whole. We also look at the issue of subsample instability and the choice of priors. Section 6 concludes.

2 Methodology

In this section, we present the two competing approaches in the literature—the level- and first differences-based hours SVAR models. Then, we propose a new test to disentangle for the level-first differences specification of hours. Finally, we specify our priors and the information criteria used in the sequel.

2.1 The structural VAR procedure

We briefly review a version of the Blanchard and Quah (1989) structural VAR procedure used by Galì (1999, 2004) and Christiano, Eichenbaum and Vigfusson (2003).

Let consider a reduced vector autoregression of the form

$$A(L)X_t = u_t.$$

where the errors terms have variance-covariance matrix Σ and are orthogonal at all leads and lags. The vector X_t is given by $(x_{1t}, x_{2t})'$ where x_{1t} is the first difference of the log of labor productivity and x_{2t} is a measure of the labor input.

Since this is a reduced form of an economic model, the error terms have no structural interpretation. To interpret this shock, it is convenient to invert this vector autoregression in order to express it as a vector moving average process

$$\begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} C_{11}(L) & C_{12}(L) \\ C_{21}(L) & C_{22}(L) \end{bmatrix} \begin{bmatrix} e_{xt} \\ e_{ht} \end{bmatrix}.$$

where $e_{x_{1t}}$ and $e_{x_{2t}}$ are serially uncorrelated, orthogonal structural disturbances, whose variance is normalized to unity. The polynomial $|C(z)|$ is assumed to have all its roots outside the unit circle to rule out non-fundamental representations.

To identify the structural parameters from the reduced form parameters, Galì (1999) assumed that the first shock $e_{x_{1t}}$ has a permanent effect on labor productivity whereas the second shock $e_{x_{1t}}$ has no permanent effect on this variable. In this respect, permanent shocks to productivity are interpreted as technology shocks and the transitory shocks can captured demand effect and other driving forces behind output and labor input fluctuations. For the rest of the paper, we interpret it as a demand shock.

Given this approach, two specifications are considered in the literature. On the one hand, Galì (1999) assumes that x_{2t} is the first-difference in the log of the labor input (h_t), so that the reduced form is defined by

$$A(L) \begin{bmatrix} x_{1t} \\ \Delta h_t \end{bmatrix} = u_t$$

whereas CEV (2003) consider a level specification where x_{2t} is the log of labor input

$$A(L)\begin{bmatrix} x_{1t} \\ h_t \end{bmatrix} = u_t.$$

These two competing models yield two opposite conclusions regarding the effect of a positive technology shock. In effect, while Galì (1999) claims that a positive shock to technology leads to a persistent and statistically significant fall in hours, CEV find that hours significantly rise. This implies, in turn, different responses to the question of the main force driven business fluctuations. Many recent papers have examined the robustness of these results (see, for example, Chari, Kehoe and McGrattan, 2004) but none, to our knowledge, has tried to propose a test, which encompasses the two specifications.

2.2 A new specification test

To disentangle for the level/first difference debate surrounding the labor input measure, we develop a new test based on the following specification

$$A(L)\begin{bmatrix} x_{1t} \\ \Delta h_t \end{bmatrix} + Ch_{t-1} = \begin{bmatrix} u_{x_{1t}} \\ u_{h_t} \end{bmatrix}.$$

On the one hand, if the C matrix is null, then the first-difference specification of CEV is recovered. On the other hand, if the C matrix is non null, then our test provides evidence for the level specification of Galì. Level hours in this context, or rather its deviation from mean, can be thought of as an "error correction term" driving employment/output back towards trend.

To test such restrictions on the C matrix and to estimate the different models, we use a Bayesian methodology. This is motivated by the following points. First, as it is well-known, accurate estimations of he finite sample distributions of (A, C, Σ) is important for applications of the SVAR methodology. However, such finite sample distributions of OLS estimators of the parameters of interest are unavailable. On the other hand, asymptotic theory may pose some problems. VAR model generally involves a large number of parameters, and the data size is not enough large to justify the use of such theory. In this respect, adding objective or subjective prior information to the data allows us to get back some degrees of freedom that might be lost from estimating an otherwise realistic number of VAR coefficients.[4] Second, since we wish to estimate the impulse-response functions, the variance decomposition, and the conditional correlations of interest, Kilian (1999) shows that the asymptotic theory involves approximation of nonlinear functions, but this approximation becomes worse the more nonlinear the functions there are. One way to

[4]It is perfectly possible that some variables may enter any given equation of the VAR in the "true" model, but others might not. In particular, hours might be best modelled in levels, but level hours might not enter into some or all of the other equations of the VAR (or at least not prominently enough to be distinguished from sampling error). Hence if the difference restriction were imposed, a classical model selection criterion such as the Akaike information criterion or the Schwarz criterion might strongly accept the difference specification, simply because of the greater parsimony, when the true model included level hours. Clearly, the resulting "best" model would be misspecified; the proper specification winds up being thrown out with the excessive parametrization.

attenuate this problem is to use classical bootstrapping methods. However, the Bayesian techniques used here yield exact finite-samples densities of the features of interest and includes the uncertainty. As is shown by Koop (1992), the measures of uncertainty are larger than their classical counterpart. Furthermore, Sims and Zha (1995) show that Bayesian approach gives a sound basis to the computation of error bands of impulse responses functions. Third, as is pointed out by Phillips (1998), impulse responses functions (as well as variance decomposition, etc) which are estimated from unrestricted VARs with roots near unity yield inconsistent estimates. Given that the main issue here is to choose among a a VAR specification with a unit root in hours against a stationary representation of the labor input measure, our Bayesian approch allows us to tackle this problem. In effect, classical inference on unit root differs substantially from the Bayesian one. In particular, as illustrated by Sims and Uhlig (1991) and established by Uhlig (1994), the conditional likelihood function as a function of the model parameters is not affected by the presence of unit roots, similar results hold for the conventional t and F statistics in their Bayesian interpretation. At the same time, since a Bayesian estimator of (A, C, Σ) depends on the sampling distribution, the prior and the loss function, suspicion can occur given some priors must be postulated. Nevertheless, we deal with this issue in two different ways. On the one hand, we assess the robustness of our results using different sets of priors. On the other hand, we use the contributions of Phillips and Ploberger (1996) and Phillips (1996) in which they develop a theory which reduces the weight of the priors (for a given set of parameterized priors), by optimizing a well-chosen criterion over this prior family. Moreover, Phillips and Plovergers (1996) derive a limiting representation of the Bayesian data density that is of the same general exponential form for a wide class of likelihood functions and prior distributions. This result is not affected by the presence of unit-roots. Fourth, as is explained below, we use a Laplace approximation of the Bayes factor and the PIC criterion to conduct inference on the paramters of interest. However, we do not impose a priori values of the hyperparamters but rather maximize the respecting criteria. This approach allows us to test the robustness of our results over different sub-periods and to relax common criticisms of the Litterman priors etc. Finally, the recent developments of Bayesian econometrics have conducted to similar efficient tests for the order of cointegration (Kleibergen and Paap, 2002; Strachan and Inder, 2004).

2.3 The Bayesian approach

2.3.1 Priors selection

Our Bayesian VARs use a random walk prior inspired by the Minnesota prior suggested by Litterman (1986), imposed on a classical VAR by combining the VAR likelihood with a Normal-Wishart prior distribution as suggested by Kadiyala and Karlsson (1997).

Let $\beta = vec(A)$ where B is the $(c_{\max} + m \times l_{\max}) \times m$ matrix of coefficients of a VAR with m equations, $l_{\max}$ lags and $c_{\max}$ deterministic variables. Given the covariance matrix of the residuals Σ_ε, assume β to have a multivariate normal prior distribution $\beta|\Sigma_\varepsilon \sim N(\beta_{prior}, \Sigma_\varepsilon \otimes \Omega_{prior})$ and the prior distribution of the $m \times m$ disturbance covariance matrix Σ_ε to be inverse Wishart with α degrees of freedom, i.e. $\Sigma_\varepsilon \sim IW(\Sigma_{prior}, \alpha)$, giving Σ_ε a prior mean of $\frac{1}{\alpha - m - 1} \times \Sigma_{prior}$. The Normal-Wishart prior is particularly easy to use inasmuch as combining the priors with the likelihood implied by a VAR using T data points results in a Normal-Wishart posterior,

$$\beta|\Sigma_\varepsilon \sim N(\beta_{post}, \Sigma_\varepsilon \otimes \Omega_{post})$$

where $\Omega_{post} = \left(\Omega_{prior}^{-1} + X'X\right)^{-1}$and $\beta_{post} = \Omega_{post}\left(\Omega_{prior}^{-1}\beta_{prior} + X'X\beta_{OLS}\right)^{-1}$,

and

$$\Sigma_\varepsilon \sim IW(\Sigma_{post}, T+\alpha)$$

where $\Sigma_{post} = B_{OLS}'X'XB_{OLS} + B_{prior}'\Omega_{prior}^{-1}B_{prior} + \Sigma_{prior} + (y - XB_{OLS})'(y - XB_{OLS}) - B_{post}'\Omega_{post}^{-1}B_{post}$.

One advantage of the Normal-Wishart posterior is that it makes drawing from the posterior distribution and calculating moments on interest straightforward.

The variance-covariance matrix is assumed a priori to be diagonal with a mean of $diag(s_1^2, ..., s_m^2)$, where s_i^2 is the variance in the disturbances of the ith equation estimated with a diffuse prior (that is, the corresponding equation from a classical VAR). Hence we set Σ_{prior} to be the diagonal matrix $(\alpha - m - 1) \times diag(s_1^2, ..., s_m^2)$. The degrees of freedom parameter α from the Inverse-Wishart prior will serve as one of the hyperparameters of the prior, imposing more or less strictly the constraint that the posterior covariance matrix is diagonal. As in our case the cross correlations of the disturbances are crucial to the results, we do not want to set that restriction too strictly; hence we set $\alpha = m + 2$, which ensures that the prior mean exists but adds relatively little information to the data.

The mean of the Minnesota prior is a random walk, hence β_{prior} is set so as to give the first autoregressive lag of each series entering the VAR in differences a prior mean of zero, while the first autoregressive lag of each series entering the VAR in levels is given a prior mean of one. The prior means of all other elements of β, including non-autoregressive lags and autoregressive lags beyond the first, are given a prior mean of zero, as are the prior means for the deterministic variables. Ω_{prior} is given as a diagonal matrix so as to set the mean for the prior covariance matrix of β, $\Sigma_\varepsilon \otimes \Omega_{prior}$, to be a diagonal matrix with element $\sigma_{ij,l}^2$ corresponding to the lth lag of variable j in the ith equation being:

$$\begin{aligned} \frac{\lambda_0^2}{l^{\lambda_1}} \quad for\ i &= j, \forall l \\ \frac{\lambda_0^2}{l^{\lambda_1}}\left(\frac{s_i^2}{s_j^2}\right) \quad for\ i &\neq j, \forall l \end{aligned}$$

and the elements σ_{ic}^2 corresponding to the deterministic variable c in the ith equation being $\lambda_0^2\lambda_2$ for all c.

The overall tightness hyperparameter λ_0 gives the prior standard deviation for the first autoregressive lag; the ratio of variances serves to scale up or down the tightness for non-autoregressive lags. The hyperparameter parameter λ_1 tunes the rate at which the tightness of the imposition of the prior mean increases with increasing l. Finally, λ_2 tunes the tightness of the imposition of the zero prior mean on the coefficients of the deterministic variables.

Given a specification, and with the posterior distribution of various candidate models in hand, it is fairly straightforward to calculate posterior distributions of moments of interest such as impulse-responses, conditional correlations, variance decompositions, and so forth, in the fashion suggested by Koop (1992). For each of a large number of draws (10000 draws in most of the exercises described here) from the posterior distribution for the disturbance covariance matrix and corresponding draws from the conditional posterior distribution for the VAR coefficients, we compute the moments of interest conditional on those draws, and from those draws obtain posterior distributions. The derivation of the BQ impulse responses to technology were calculated using the Cholesky-decomposition method suggested by Keating (2002), with technology shocks assumed to be the only shock with a permanent effect on productivity levels.[5]

2.3.2 Specification test

The prior means on each coefficient in the C vector is taken to be zero (i.e. the "null hypothesis" is that the difference specification is correct) and the prior covariance of the term in C corresponding to the ith equation is $\lambda_3^2\left(\frac{s_i^2}{s_h^2}\right)$, where s_h^2 is the disturbance variance from the hours equation of the classical VAR.

As an optimal Normal-Wishart prior is highly informative on the coefficients of the VAR, it is possible that it could affect the results. Therefore, we also specify noninformative priors to assess the robustness priors (see further). In a similar context, this is the methodology used by Kleibergen and Paap (2002) to test the order of the cointegration.

In what follows, the VAR using differenced hours only, imposing exactly the restriction that $C = 0$, will be labelled the "differenced hours VAR" (e.g. "differenced CEV hours VAR") and the VAR relaxing the zero restriction will be labelled the "level hours VAR."

2.3.3 Information criteria

Instead of parameterizing the set of hyperparameters, we maximize the lag length and the values of λ_0, λ_1 and λ_3 using two information criteria: the Laplace approximation of the Bayes factors and the PIC developed by Phillips (1996).

The Laplace approximation for the Bayes factor of model M, given data set D and a prior distribution for the vector of the model parameters θ with *pdf* f_{prior} is given by[6]

$$\ln BF_{Laplace} = \frac{d}{2}\ln(2\pi) + \frac{1}{2}\ln\left|\widetilde{\Sigma}_\theta\right| + \ln L\left(D|\widetilde{\theta}, M\right) + \ln f_{prior}\left(\widetilde{\theta}|M, \alpha, \lambda_0, \lambda_1, \lambda_2\right)$$

where $d = m \times (c + l \times m) + m \times \frac{m+1}{2}$ is the dimension of the model, and $\widetilde{\theta}$ is the value of θ at the posterior mode, with $\widetilde{\Sigma}_\theta$ being the Hessian matrix of second derivatives at $\widetilde{\theta}$.

In this paper, we approximated the posterior mode of θ with the posterior mean and $\widetilde{\widetilde{\Sigma}_\theta}$ with the posterior mean of the covariance matrix.[7] As the hyperparameters are few in number, we find their optimal values through an informal grid search for plausible values of these hyperparameters.

[5] See Annex 1.

[6] As the restriction to zero of trend productivity growth was not relevant for the post 1959 period, the value for λ_2 was set for all VARs at 10^5, to represent a diffuse prior.

[7] Ni and Sun (2002) show that, with the constant prior on the VAR lag parameters, the asymmetric LINEX estimator for the lag parameters does better overall than the posterior mean and that the posterior mean of the covariance matrix performs well in most cases. We test the robustness of our results for the lag parameter using an asymmetric loss function and do not find significant differences.

On the other hand, Phillips (1996) proposes to construct optimized VARs with data-determined hyperparameters using the following criterion:

$$PIC_{Bayesian} = -\frac{T}{2}\ln\left|\widetilde{\Sigma}_{\varepsilon|T}\right| + \frac{1}{2}\left(\ln\left|\widetilde{\Sigma}_{\beta|T}\right| - \ln\left|\widetilde{\Sigma}_{\beta|T_0}\right|\right)$$

where $\widetilde{\Sigma}_{\varepsilon|T}$ is the posterior mode of the disturbance covariance matrix given data up to time T and $\widetilde{\Sigma}_{\beta|T}$ is the covariance matrix of the coefficients of the VAR at the posterior mode. T_0 is smaller than T and is used as reference point in the computation of the criterion. It must be large enough to allow for the estimation of the model. The intuition behind this additional term is that when the variance of the prior distribution is very small, the second term of the criterion becomes larger and larger.

As previously, posterior and prior modes are approximated with posterior and prior means.

3 Data

An important issue of the hours-technology debate is the data sets. For instance, Chari, Kehoe et McGrattan (2004) argue that the impulse response functions are very different depending on the data sets they used. Furthermore, they show that the different results in the literature lie in the difference of the underlying data and not in the model. This argument has been stated in several studies (Francis and Ramey, 2002; Galì, 2004). Therefore, we use three sets of productivity and detrended hours data to estimate the bivariate BVARs:

- An index of US business productivity and an index of hours worked in the business sector deflated by population to get an hours per capita series as suggested by Christiano, Eichenbaum and Vigfusson (2003) (hereafter “CEV hours”);

- The same index of business productivity and the same hours index as in CEV, but with hours deflated into per capita terms using the corrected population series proposed by Francis and Ramey (hereafter “FR hours”);

- US real GDP and the unemployment rate (as measured by the Current Population Survey), with productivity calculated by dividing GDP by employment and detrended hours measured by the unemployment rate.

Our sample period is 1959:Q1 to 2004:Q2, except for VARs using FR hours, which use data up to 2002:Q4, the latest quarter for which Francis and Ramey’s population series is available.

We report plots of the hours per capita series in Figure 1. The stationarity of CEV hours, FR hours and unemployment are an open debate. In particular, CEV and FR hours were specifically constructed to produce a stationary measure of hours per capita. But, visual inspection suggests, to some extent, deviations from a mean, if any exists, are long and persistent. Also FR hours appears to exhibit a slight upward trend during the post 1959 period. One standard argument to invoke the stationary of hours works per person series is to say that in all economic models this series is bounded and thus the stochastic process for hours cannot literally have a unit root (see CEV). At the same time, one counterargument could be that the unit root specification can be best viewed as statistical approximation for variables with high correlation (see Francis and Ramey, 2003; Chari, Kehoe and McGrattan, 2004).

While the latter position can be defended, one limitation is that the implications of a near-unit root and a unit root are sharply different in a VAR models for impulse-response functions, variance decompositions, etc. At the same time, due to the low power of standard unit roots, no conclusion can be drawn from such tests. In this respect, one advantage of our Bayesian setting is that it is no more sensitive to the unit root problem.

(*Insert Figure 1 around here*)

4 Results of bivariate VARs

In this section, we present the results in the case of bivariate VAR models. More specifically, we discuss the specification choice, the impulse-response functions, the variance decompositions, the conditional correlations, and the dynamics of the shocks.

4.1 Specification choice

Results are reported only for VARs calculated with one deterministic variable (a constant) and lags of each series of productivity growth and detrended hours.

Tables 1(a)-(b) report optimal lag length, hyperparameter values, PIC and Laplace Bayes factors for the bivariate Bayesian BVARs. For CEV and FR hours the optimal lag length of three is more in line with those regularly used in VAR exercises; for unemployment, it is more conservative, with two lags being best. The values for the overall tightness parameter and the lag decay parameter are not far from Litterman's original suggestions of $\lambda_0 = 0.2$, and $\lambda_1 = 2$.

(*Insert Tables 1(a)-(b) around here*)

Our results show, first, that non-trivial absolute values of the optimal prior variance of the terms in C from zero, with values for λ_3 of around 0.025 (0.021 for FR hours). Therefore hours are clearly highly persistent, but not so persistent as to make the difference specification necessarily the true one. Second, the ratios of the Laplace Bayes factors imply for all three VARs that the level VAR is best, with probabilities from 80% (FR hours) to 89% (CEV hours). Therefore, our specification test clearly supports the evidence reported by CEV, Dedola and Nieri (2004) and Uhlig (2004); namely, hours worked enters in levels in the structural VAR model. This result is obtained with a reasonable informative prior, even one centered on the null hypothesis that the difference specification is best.

As an optimal Normal-Wishart prior is highly informative on the coefficients of the VAR (even if the Wishart prior is relatively uninformative on the variance-covariance matrix), we check whether this choice may affect the results. Therefore we made the Minnesota prior diffuse by raising the overall tightness parameter to a large number ($10^{4.5}$)

and set the lag decay to zero. We then re-estimated the Laplace Bayes factors for each specification, using (in the case of the level specification) optimized values of the tightness parameter on C.[8] Table 2(a) provides evidence that the results using the "Diffuse-Wishart" prior are qualitatively similar to those for the more informative Normal-Wishart. The most importance difference is a doubling of the Bayes factor in favor of the level model, to the degree that the difference model is always rejected.

Finally, in the last section, we test the robustness of this result using other informative or other noninformative priors. Conclusions are similar, that is, we find strong evidence for the level specification.

(*Insert Table 2(a) around here*)

4.2 Impulse response functions

Figures 2 through 4 depict the 95% confidence bands for the impulse responses of output and hours under either the level (black) and difference (red) specification. Consistent with the results reported in Christiano et al., the median IRFs, for each variable of interest (output and hours) from the differenced model is well in the tail of the posterior distribution of the IRFs from the level model, and *vice versa*, neither median being well-nested in the other model's 95% confidence band.

(*Insert Figures 2-4*)

As it is clear to the eye, the 95% confidence bands, however, do suggest that unbiasedness in the IRFs comes at a large cost in precision. For all three bivariate VARs, the 95% confidence bands for the effect of a technology shock on impact on hours significantly nests zero, making settling the technology-hours debate difficult no matter which measure of employment we trust the most.

4.3 Variance decompositions

Given the relationship between IRFs and other moments often used to evaluate the role of technology shocks in cycles, such as variance decompositions, it is worth looking at just how large the cost of unbiasedness can really be for other moments as well.

In this respect, Table 3(a) follows CEV by reporting variance decomposition results for the bivariate VAR using business productivity and CEV hours. Our studies of variance decompositions, and the examination of the shocks themselves below, will in this paper only report results from the CEV hours VARs. This is in part to save space, and also because much of our purpose here is to demonstrate the lack of information structural VARs can supply regarding the technology-hours debate.[9]

[8]We also re-estimated the PIC criterion. Since the results look similar, we do not report them.

[9]Other results are available on request.

(*Insert Table 3(a) around here*)

We do go beyond Christiano et al. (and for that matter scores of other papers reporting similar variance decompositions), however, and report a 95% confidence band for the percentage of variance in output and in hours explained by BQ-decomposed permanent "technology" shocks. The posterior median of the distribution paints a substantially similar picture to that of Christiano et al. More specifically, 76 percent of output disturbances in a given period can be accounted for by technology shocks, with the percentage slowly rising to 100 percent (by construction) as the lag length increases (following Christiano et al., we report results for one, four, eight, twelve, twenty and fifty steps ahead). The explained fraction of variability in hours is generally below 15% with 50% probability in the short term (less than four quarters). The median amount of hours fluctuations caused by technology shocks is much higher in the long term: at business cycle frequencies (two to five years ahead), the median suggests that around 25 to 35 percent of hours fluctuations can be explained by technology. Strikingly, this finding is pretty much in line with the results reported in Galì (1999). Therefore it may appear that the bulk of movements in hours worked should reflect shocks different from those affecting technology.[10]

Nevertheless, the distributions of the reported percentages suggest more caution regarding the interpretations of the previous results. While, again, the median estimate of the percentage of output movements caused by contemporaneous technology shocks is 76 percent, we cannot (with 95% confidence) rule out figures as low as 21 percent nor estimates as high as 99 percent. The problem is apparently less severe at business cycle fluctuations, with (say) at twelve steps ahead, no less than 60 percent of output fluctuations can be explained by technology.

However, similar problems exist for hours, and get worse and worse as time horizons expand. Again, the median estimate of the percentage of hours fluctuations caused by contemporaneous shocks to technology is 6 percent; however, estimates as low as zero and as high as 47 percent cannot be ruled out. At business cycle frequencies the 95% confidence band widens to the point where useful inference becomes almost impossible; possible values range from zero to over 80 percent. Clearly, the productivity and hours data alone, restricted only by the BQ-identification scheme do not have much to say on what the contribution of technology shocks might be to fluctuations in employment.

The great uncertainty in the variance decompositions is closely related to that plaguing the impulse response functions, with the 95% confidence bands nesting both very large and very small responses of output and hours to technology shocks, ranging from responses near 100% of the typical size of an output disturbance to near zero percent. In this respect, while we can be fairly sure the CEV BVAR with level hours per capita is relatively free of specification error (and the bias of unknown form that might result), the cost in precision seems too large. Therefore, the data appear to be compatible with almost any hypothesis regarding the importance (or lack thereof) of technology shocks in business cycles. This finding supports to some extent the conclusion of Galì (1999) regarding the role of technology shocks as the main source of business fluctuations.

[10]Note that we obtain the same results if we estimate a first-differenced VAR.

4.4 The shocks themselves and conditional correlations

Given the uncertainty of the variance decomposition results, one would like another way to assess the relationship of our identified technology shocks to disturbances in economic variables (such as hours). One way is to calculate a posterior distribution for the technology shocks identified from the BQ-decomposition scheme, as well as for the disturbances in economic variables of interest.

Given a draw for the coefficients of the VAR B^* and the disturbance covariance matrix Σ_ε^*, we can construct a draw for the matrix of residuals from the equations of the VAR ,

$$u^* = y - XB^*,$$

where X is a $T \times (c + m \times l)$ matrix of the values of the deterministic variables and the lags of the endogenous variables at each time point, and the $T \times m$ matrix y represents the present values of the VAR variables at each time point.

Given B^* and Σ_ε^*, e^* is a linear function of the permanent technology shock Δz and the other shocks u, both in standard deviation terms, namely

$$\begin{bmatrix} \Delta z \\ u \end{bmatrix} D = e,$$

where the decomposition matrix D is a function of B and Σ_ε, so that the draw for the technology shock vector Δz^* is simply the first column of

$$\begin{bmatrix} \Delta z^* \\ u^* \end{bmatrix} = D\left(B^*, \Sigma_\varepsilon^*\right)^{-1} e.$$

As we do not interpret the other structural shocks calculated by the Cholesky-decomposition algorithm, we collect a posterior distribution only for Δz, as well as for its correlations at up to five leads and lags with disturbances in productivity growth and in hours. The 95% confidence intervals for the values of Δz in the bivariate CEV VAR are given in Figure 5, while the conditional correlations are given in Tables 4(a)-(b). The dynamics of the technology shocks from the bivariate VAR do suggest substantial negative shocks around the periods of well-known recession periods, most obviously around 1974-75 and 1979-82. The median correlation between the identified technology shocks and disturbances in productivity growth is extremely high (around 0.975), and the correlation is almost certainly no lower than 0.75. The correlation of technology shocks with disturbances in hours, however, like the hours IRF, is much less suggestive of an overwhelming role of technology shocks in changes in hours. The median correlation is weakly positive (0.20), but the 95% confidence band nests zero, with possible values as low as -0.34 and as high as 0.68.

To sum up, our Bayesian specification test provides evidence for the level hours VAR whatever the data sets we considered. This confirms the conclusions of CEV, Dedola and Nieri (2004) and Uhlig (2004). At the same time, the uncertainty surrounding the impulse response function, the variance decompositions, and the conditional correlations cast doubts on the role of technological shock as being the primary source of business fluctuations. Especially, the fraction of variability in hours worked explained by technology shocks is rather weak. This confirms the Gali's (1999) results.

(*Insert Tables 4(a)-(b) around here*)

(*Insert Figure 5 around here*)

5 Robustness Issues

In this section, we test the robustness of our results. To do so, we experiment larger VAR specifications—using the models of Christiano et al. (2003) and Galì et al. (2003)—and we examine the impulse-response functions, the variance decomposition, the conditional correlations, and the dynamics of shocks. Furthermore, we analyze whether our results might be driven by the changes of monetary policy in the United States and whether inference with Canadian data yields similar results. Finally, we address the issue of informative priors *versus* non informative priors.

5.1 Results from larger VARs Specification

The advantage of the level specification becomes clearer when larger VARs are used. In Table 1(c) we report optimal hyperparameters, lag lengths and approximate Bayes factors for six-variable VARs containing each measure of productivity and hours and the following other variables (following, with one exception, Christiano et al. 2003):

- The ratio per quarter of nominal gross private domestic investment and durable consumer goods purchases to GDP ("investment/output ratio");

- The ratio of nominal domestic demand (C+I+G) to nominal GDP, which, when logged, gives an approximate percentage of the trade deficit as a percentage of GDP[11];

- The rate of change of the GDP price deflator ("inflation");

- The quarterly average of the federal funds rate ("federal funds").

[11] Christiano et al. (2003) actually use a measure of the consumption-output ratio, constructed as the ratio of nondurable spending plus nominal government purchases divided by nominal GDP. However, they assume implicitly that (i) all government purchases are consumption and (ii) public consumption is equivalent, dollar for dollar, with private consumption. Both assumptions are discussable. Therefore, since the investment enters in the specification of the SVAR, we prefer using the following measure, $\frac{C+I+G}{GDP}$. As a practical matter, the qualitative results reported here are not so much affected by using one instead of the other. Results (with the Christiano et al. specification) are available on request.

(*Insert Table 1(c) around here*)

Table 1(c) details the optimal hyperparameter values for the six-variable VARs using various measures of productivity and hours, and the Bayesian PICs and Bayes factor ratios associated with each one. Again, for the CEV and FR BVARs, estimated with levels or differences, three lags of productivity and hours seem to be optimal, while two lags appear to be best for the unemployment BVAR. A rather tighter constraint around zero for the VAR parameters appears best for the larger VARs ($\lambda_0 \approx 0.09$), in part because of the larger number of extraneous lagged variables. However, a somewhat looser lag decay is best ($\lambda_1 \leq 1$).

Again, as well, the 6-variable VARs favor a level specification for hours. For CEV hours and unemployment, in particular, the advantage of the level specification is decisive; the posterior probability of the difference specification being best is less than one percent for CEV hours and about 0.01% for unemployment. For FR hours, however, the advantage of the level specification actually falls; the differenced model has about a probability of 40% of being the true model. Also, given the level model, the best value for the constraint around the zero prior mean of the C vector a bit smaller for FR hours ($\lambda_3 \approx 0.015$) than for CEV hours or unemployment ($\lambda_3 \approx 0.03$).

As previously, to check the robustness of these results, we re-conduct our specification test using a "Diffuse-Wishart". Table 2(c) shows that the Normal-Wishart prior is slightly more informative for the six-variable VAR model than for the bivariate VARs at the optimal overall tightness parameter. There are some differences when we compare the results of Table 2(b)—informative priors—versus Table 2(c)—noninformative priors. However, the Normal-Wishart, in all three cases, increases the odds in favor of the level specification. However, the "Diffuse-Wishart" clearly favors the level model for all three specifications, so that the qualitative results are not changed.

(*Insert Tables 2(b)-(c) around here*)

5.1.1 Impulse responses and investment

Figures 6 through 8 report the impulse responses from the six-variable VARs using each measure of hours. All three sets of IRFs are broadly similar, in that the median responses of economic variables to the identified permanent shocks do not resemble most accounts of the stylized facts of US business cycles, viz. output should rise, employment should rise and investment should also rise farther than output as a whole. Certainly it is far from obvious that employment should rise in response to the permanent shock; as with the bivariate VARs, the 95% confidence bands for the effect on impact of the permanent shocks on hours or employment comfortably nest zero. For the CEV hours VAR, for example, hours only rise after a permanent shock 67% of the time. In the six-variable VARs, it is worse in that for all three hours series even the sign of the effect on output on impact is not obvious (that is, the confidence bands nest zero even for output). On the credit side, the output effect clearly turns positive after two or three quarters; however, the effect on hours is not obviously positive even up to twelve quarters ahead.

(*Insert Figures 6-8 around here*)

Also, investment does not obviously rise farther than output, as we would see in a business cycle. For the CEV hours VAR, for example, the investment/output ratio only rises in response to a permanent shock about 26 percent of the time. The IRFs for investment itself casts into doubt even the sign of the effect on technology on investment, even up to twelve quarters ahead. What does appear to be a strong effect of permanent shocks is on inflation, at least for CEV hours and unemployment (the effect is less strong for FR hours), the effect of permanent shocks on inflation is negative more than 99% of the time.

For federal funds and the trade deficit, the effects are less obvious. The confidence bands for the effect on impact on the nominal federal funds significantly nests zero, but becomes more and more negative with growing horizons as inflation expectations, as much of the central bank as of the marketplace, slowly fall. As a result, in the short run real interest rates rise. Higher real interest rates and lower investment/output ratios (i.e. higher consumption) make the apparent decrease in the trade deficit/GDP ratio on impact (98% of the time) rather puzzling, however, though this fairly strong effect gets weaker with increasing horizon.

A technology shock should, of course, raise real interest rates as the productivity of capital rises. However, if the identified permanent shock does model technology shocks fairly well, then the wealth effect of a technology shock clearly dominates the substitution effect, with consumption apparently outstripping investment, and the positive employment effect from higher productivity more or less counteracted by the negative employment effect from higher wealth. The jump in consumption, faster than output as a whole, may partly explain the sharp negative effect on inflation. Many models of money demand (cash-in-advance models, for example) underline the relation of money demand to consumption, which is boosted by a technology shock. Hence the price level ought to fall in response to a technology shock. It does suggest, however, that monetary policy in the US might not have been sufficiently accommodating to technology and other supply shocks (an obvious example is during the money-growth targeting experiment in the 1979-1982 period) to prevent a drop (or rise) in prices in response to a positive (or negative) aggregate supply shock, and possibly the resulting falls in employment through new Keynesian Phillips curve effects. A natural question (explored farther below) is whether that sharp negative response disappears after 1982.

5.1.2 A reappraisal of Galì et al. (2003)

The level specification is also strongly favored with a four-variable VAR in productivity, CEV hours, inflation and federal funds, similar to that used by Galì et al. (2003). The impulse response functions of this four-variable VAR (reported in figure 9) have different implications for the response of hours to technology, however. Consistent with the results in Galì's work on this subject, the optimal four-variable VAR without investment results in a 90% probability of a technology shock having a negative effect on hours on impact, an apparently strong finding for such a negative effect. The result, however, dissipates when we look at the six-variable VAR including investment and trade deficit data.[12] For the six-variable VAR the probability is about 75% in favor of a positive effect of technology on hours-inconclusive, but for all that illustrative of how sensitive the results of Galì and his various co-authors is to inclusion of investment. Possibly this implies that a structural VAR model of the macroeconomy without investment

[12]A five-variable VAR without the trade deficit does not lead to very different results; inclusion of investment is what is crucial.

is misspecified, a related problem to the problem of capital as an omitted variable pointed out by Chari et al. (2004) and McGrattan (2004), who caution against use of structural VARs partly on these grounds.

(*Insert Figure 9 around here*)

5.1.3 Variance decompositions

Table 3(b) reports the variance decompositions for the six-variable VAR, while table 3(c) reports those for the four-variable VAR. As both lead to substantially similar conclusions regarding what we can learn about technology's role in business cycles, we will only discuss in detail the variance decompositions from the six-variable BVAR. Again, the posterior median estimates delivers a picture substantially similar to that painted by Christiano et al. The amount of output fluctuations caused by contemporaneous technology shocks falls from 76 percent to 10 percent; the amount caused by those shocks twelve steps ahead falls from 95 to 62 percent. The amount of hours fluctuations is about the same at short horizons and actually somewhat higher at long horizons (49 percent five years ahead, as opposed to 36 percent in the bivariate VAR). Particularly damning is the low percentage of investment (the bulk of output fluctuations in most business cycles) that technology shocks can explain at business cycle frequencies (at the median, at any rate), with the median estimate being only 20 percent three years out. The median estimates show similar stories for federal funds and for the trade deficit. Technology shocks, as Christiano et al, do seem to do a better job (at the median) explaining inflation, with the median estimator of the proportion of inflation explained by technology being 64 percent three years out.

(*Insert Tables 3(b)-(c) around here*)

These estimates, however, must all be taken with a grain of salt when the large confidence bands around them are taken into account. If anything, these bands are wider than those for the bivariate VAR. The amount of contemporaneous output fluctuations that might be explained by technology shocks is anywhere from 0 to 44 percent; three years ahead that proportion could anywhere from seven percent to 93 percent! The situation for hours is not much better (zero to 69 percent), and similar stories exist for all the variables in the VAR (investment, zero to 76 percent; inflation, 16 to 89 percent; federal funds, zero to 60 percent; trade deficit, 0 to 30 percent). Clearly, the structure imposed on the data by the six-variable VAR is inadequate to allow meaningful inference about the role of technology shocks for any of these variables using just the variance decompositions.

5.1.4 The shocks themselves and conditional correlations

Hence, we go back and look at the posterior distribution of the permanent shocks from the larger VARs and their correlation with the disturbances in economic variables. The posterior distribution of the shocks from the four-variable VAR using CEV hours (Figure 10) and that from the six-variable VAR using CEV hours (Figure 11) lead to two results. First, neither look nearly as much like the US business cycle pattern than the shocks do from the bivariate VAR. Second, as the IRFs suggest, the variance of the ”technology shocks” grows during the high-inflation period of the 70's and diminishes during the low-inflation of the 80's and 90's.

(*Insert Figures 10-11 around here*)

Tables 4(b) and 4(c) report the 95% confidence bands for the conditional correlations of the identified permanent shocks with inflation, as well as productivity growth and hours. One difference between the correlations from the four-variable VAR and the six-variable VAR is the median correlation of technology shocks with hours disturbances; the four-variable VAR suggests a negative correlation (-0.35), while the 6 variable VAR suggests a positive one (0.13). However, the 95% confidence bands for both clearly nest zero. Another difference merely highlights a difference of both from the bivariate VAR. The four-variable VAR displays a much weaker correlation (median 0.58) of permanent shocks with productivity growth disturbances than does the bivariate VAR. However, that from the six-variable VAR is even weaker (median 0.31), weak enough that a zero correlation cannot be ruled out.

(*Insert Tables 4(b)-(c) around here*)

What the four- and six-variable VARs do agree on, consistent with the evidence of our visual inspection, is a fairly tight, negative relationship between permanent shocks and inflation disturbances. The median correlation for both VARs is about 0.75, with the six-variable VAR differing mostly in its tighter 95% confidence band, being more insistent on the negative effect of technology on inflation than Galì et al.'s four-variable VAR.

5.2 Has the US economy's (or the Fed's) response to technology shocks changed over time?

Throughout our analysis, we have implicitly assume that there has been no structural change. However, authors like Galì, Lopez-Salido and Valles, among others, have argued that systematic monetary policy have changed after 1979, and that resulted in a structural change in VARs parameters and in the effects of technology shocks, especially on hours worked. Fernald (2004) shows that, once allowing for statistically and economically plausible structural breaks in labor productivity, hours worked fall after a technology shock whether this series enters the VAR in levels or in first-differences. In contrast, Dedola and Nieri (2004) argue that the hours response of a technology shock is hump-shaped and does not depend on the presence of a trend break in data. To further assess the robustness of our results, we examine the issue of subsample stability.

All the experiments above have used the full 1959-2004 data set. To check if the responses of economic variables (including inflation) to technology shocks has changed over time, and to verify where that structural shift might have been, we conducted the following experiment. We began by taking a thousand draws from the six-variable VAR estimated using productivity and CEV hours from 1959:Q1 to 2004:Q2, and calculating the posterior probabilities of a positive response of each variable in the VAR (productivity growth, hours, trade deficit/GDP ratio, investment/output ratio, inflation and federal funds). We then re-estimated the six-variable VAR, leaving hyperparameter values constant, but this time dropping the first observation off the beginning of the data set, so that our data set ran from 1959:Q2 to 2004:Q2, and re-estimated the posterior probabilities of positive responses to permanent shocks. The rationale behind this *diminishing window* approach is that if there had been a large change in regime around

1979-1982, the farther in the past an observation was, the less likely it was to be relevant for estimating the current regime.

(*Insert Figure 12 around here*)

The resulting series for the posterior probabilities for positive responses is given in Figure 9; the year ticks indicate the starting point of the data set used to calculate each probability. The posterior probability of a positive effect of inflation on a technology shock shoots up from about 5 percent to 20 percent; that is, we can no longer conclusively state that technology shocks lower inflation if we look just at the post-1984 data. With post-1984 data, a positive permanent shock also more insistently raises productivity growth on impact (96 percent probability), while the high probability of a lower trade deficit from a permanent shock disappears once data before about 1974 are dropped.

If, however, we look at the impulse responses to technology shocks from a six-variable VAR estimated using only post-1984 data (given in Figure 6), it is not obvious that we can attribute the lowered inflation volatility to markedly improved monetary policy.[13] The most marked change in the IRFs as compared to those estimated for the full sample is that the inflation response is no longer unambiguously zero. However, there is at least reasonable doubt that monetary policy's response to technology shocks has changed much at all. The median response of the federal funds rate does seem to fall more quickly to accommodate lowered inflation expectations than did the median response from the VAR estimated with the full data set. The confidence bands are, however, extremely wide, and would comfortably nest the median federal funds response from the VAR with the full data set.

Our results show that the post-1984 IRFs are inconclusive in the sense that, after a technology shock, the effects on hours and even on output remain ambigguous,and even the fairly strong negative effect of technology on the trade deficit disappears. While, again, technology shocks do not obviously give us a business cycle, the contrary cannot be ruled out either. While monetary regimes may well have changed, a very real risk in using only post-1984 data to calculate the effects of permanent technology shocks on output is that we may wind up throwing out most of the information the data have to offer on the economy's behavior during business cycles. Given that the two recessions during the post-1984 period were rather mild, it is actually little wonder IRFs have so little to say about the causes of business cycles when we use only post-1984 data, given that even the full data set, giving information from the much more volatile Sixties and Seventies, can give us only slightly less vague inferences. Supplementing the data with an atheoretical Bayesian prior, though it might help avoid serious specification errors, are not enough to make the data speak enough.

To further assess the subsample stability, we re-estimate the probabilities of a positive response after a technology shock using an increasing rolling-over window. Furthermore, we use a diffuse-Wishart (noninformative) prior. The

[13]The BVAR used to calculate these IRFs is slightly different from that used to determine the posterior probabilities of positive effects. With a shorter data set, the optimal lag length and hyperparameter values for the six-variable VAR change somewhat. The "best" BVAR is now with two lags, an overall tightness parameter of 0.113 and a lag decay parameter of 1.70. As hours is no longer so obviously stationary over the post 1984 period, the tightness of the C vector around zero must be tighten somewhat, with the hyperparameter falling to 0.013.

pre-sample is 1959-1983. Figure 13 depicts the results for the level SVAR with CEV data. To compare the results, we update Figure 9 to take into account a diffuse-Wishart prior. The corresponding probabilities are presented in Figure 14. The main conclusion is that the data after 1984 do not update the posterior medians of the signs of the responses to technology shocks very much. However, the size of output fluctuations after 1984 is somewhat smaller than those before, suggesting that a researcher, before looking at post-1984 data, would be given strong prior beliefs by the pre-1984 data. This could be misleading if there has been a regime shift. Therefore, the results from the increasing rolling-over window might be dominated by the pre-1984 observations. In contrast, the decreasing window-based procedure amounts to loosening the prior beliefs implied by the pre-1984 data.

(*Insert Figures 13-14 around here*)

A few patterns are also worthy of note. First, the trend of the probability of a positive response of the investment output ratio to a technology shock trend upwards in the decreasing window regressions; in the post-1984 period the probability is about 0.9. To the degree the identified permanent shocks measure true technology shocks, the post-1984 business cycle seems to look more like a technology-driven cycle, suggesting perhaps, that demand-side shocks have been reduced in the post-1984 period. Second, the response of hours is going from mostly positive in the full sample to mostly negative (probability of a positive response to technology os about 0.2) for post-1984 data. Third, the response of the trade deficit to GDP seems to reverse after 1975, going from mostly negative for the whole post-1959 period to mostly positive for the post-1984 data. Fourth, inflation's response remains negative, though this is less certain for post-1984 data. This might indicate a more accommodating monetary policy. But, as previously, all these results may only reflect greater sampling error due to the uncertainty surrounding all the nonlinear functions derived from the BVARs.

5.3 Informative or non-informative priors?

An important issue regarding the robustness of our results may be the choice of the priors. As Kadiyala and Karlsson point out, while our Normal-Wishart-based priors avoid the two main shortcomings of the Minnesota prior —the forced posterior independence between equations and the fixed residual variance-covariance matrix— the structure of the variance-covariance matrix is assumed to treat all equations symmetrically. More specifically, given the prior variance-covariance matrix, the corresponding regression parameters can only differ by a scale factor in the different equations. In this respect, the Normal-Diffuse prior, introduced by Zellner (1971), relaxes the Normal-Wishart type restrictions on the variance-covariance matrix and allows for a non-diagonal residual variance-covariance matrix. In this case, we need combining the multivariate normal prior on the regression parameters with a diffuse prior on the residual variance-covariance matrix.

The main difficulty is now that no closed form solution for the posterior moments exists and thus we use the method of Gibbs-sampling to generate the functions of interest (see Kadiyala and Karlsson, 1997). Figure 15 reports the impulse-response function of the output and the hours worked after a positive technology shock hits the economy in our benchmark bivariate VAR model. As it is clear to eye, the difference between the Normal-Wishart-based

IRFs and the Normal-diffuse-based IRFs are fairly small. The same conclusion holds for the variance decomposition, conditional correlations.[14] This result is robust to the VAR specification and to the data sets used.

(*Insert Figure 15 around here*)

To further assess the robustness of our results, we also follow the methodology of Ni and Sun (2003). The authors show that Bayesian estimators with a shrinkage prior on the VAR coefficients and the reference prior developed by Yang and Berger (1994) dominate Bayesian estimators with the diffuse prior or the Normal-Wishart prior. Therefore, we re-estimate our models and perform again our specification tests. Results are not changed: the level-based specification outperforms the first difference model. This result is robust to the data used and the subsample considered. In this respect, the degree of informativeness of our priors does not affect our main conclusions.

6 Concluding remarks

Our findings shed light on the proper way to specify structural VARs for analysis of business cycle issues; our use of Bayesian VARs and Bayesian model choice methods allow more satisfying answers in this are than classical methods could. However, we also are left with much evidence casting doubt on the practical usefulness of structural VAR analysis of the effects of technology shocks on the business cycle.

Our finding that a level specification in hours per capita and/or unemployment is favored in the Bayesian VAR models we have examined (regardless of the size of the data set), and the rejection of Galì's result that hours fall in response to a technology shock, support the results of Christiano, Eichenbaum and Vigfusson (2003), Deloda and Neri (2004) and Uhlig (2004). However, in no case is it possible, in a well-specified structural VAR, to conclude that technology shocks play a large role in business cycle fluctuations, except perhaps at very long horizons, much less find strong evidence of a positive effect of permanent "technology" shocks on employment or hours. Our results for larger VARs, in particular, imply responses to a technology shock, especially of investment, that look little like a business cycle. The distributions of impulse responses from the structural VAR (and their close relative, the variance decomposition of disturbances) are wide enough to prevent any useful inference regarding the effect of technology shocks on hours, output and especially investment. In this respect, this result support to some extent the conclusion of Galì that technology shocks might not be the primary source of business fluctuations.

The other measures of the effects of technology shocks on hours are at best only marginally more useful for assessing the role of technology shocks in the cycle. An apparent strong finding of a positive correlation of the permanent shock on productivity disturbances weakens considerably when larger and arguably better specified VARs are used. For no VAR, either, is a strong finding of either a positive or negative correlation of technology shocks with disturbances in hours.

In short, our structural VARs have little light to shed on the relationship of technology to hours, and by implication, to the business cycle in general. The appeal of structural VARs, which impose on technology shocks only that

[14] Results are not reported here but are available on request.

they alone permanently affect productivity, is that such a restriction is compatible with a wide class of DSGE models. However, in so doing, it may in fact be too unrestrictive a model; the class of models the data admits is apparently one that allows for probable roles for technology ranging from negligible to overwhelming. For any progress to be made on assessing the effect of technology shocks on employment (or anything else), researchers must look beyond the minimally theoretical structural VAR approach for additional ways of imposing reasonable restrictions on impulse responses from technology shocks.

Abandoning the structural VAR approach entirely is certainly possible, and now that the goodness of fit of Bayesian DSGE models is now competitive with that of Bayesian VAR models (e.g. Smets and Wouters 2003), results from such an approach would be more plausible empirically than they would have been in the past. However, a hybrid approach is certainly possible; a VAR model estimated with a Bayesian prior based on a more simplified DSGE model, allowing the data to make up for possible misspecification in the model, has promise for permitting answers to the technology-hours question. We leave further exploration of such approaches to future research.

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Table 1a: Laplace-Bayes factors for Bayesian VARs

	Lag Length	λ_0	λ_1	λ_3	Log Laplace (level)	Log Laplace (diff)	LB factor
Productivity (CEV Hours)	3	.24	1.80	.025	-462.61	-464.71	8.15
Productivity (FR Hours)	3	.24	2.10	.021	-452.66	-451.25	4.07
GDP per worker and Unemployment	2	.28	1.90	.025	-289.13	-287.31	6.17

Note: The Laplace-Bayes (LB) factor is defined by Laplace(level): Laplace(diff).

Table 1b: PIC for Bayesian VARs

	Lag Length	λ_0	λ_1	λ_3	Log PIC (level)	Log PIC (diff)	PIC factor
Productivity (CEV Hours)	3	.24	1.8	.025	69.44	67.61	6.23
Productivity (FR Hours)	3	.24	2.1	.021	63.76	62.53	3.42
GDP per worker and Unemployment	2	.28	1.7	.025	243.71	242.15	4.76

Note: The PIC factor is defined by PIC(level): PIC(diff).

Table 1c: Bayesian PIC-Bayes factors and their ratios for six-variable BVARs

	Lag Length	λ_0	λ_1	λ_3	Log PIC (level)	Log PIC (diff)	PIC factor
Productivity (CEV Hours)	3	.090	1.10	.031	223.84	218.09	313.15
Productivity (FR Hours)	3	.087	0.85	.015	196.78	196.23	1.73
GDP per worker and Unemployment	2	.086	.71	.033	354.05	344.95	89.14

Table 2a: Laplace-Bayes factors for Bivariate BVARs using a diffuse prior

	Lag Length	λ_3	Log Laplace (level)	Log Laplace (diff)	LB factor
Productivity (CEV Hours)	3	.029	-619.24	-616.36	17.78
Productivity (FR Hours)	3	.020	-592.88	-591.76	3.04
GDP per worker and Unemployment	2	.026	-380.17	-378.32	6.32

Note: The Laplace-Bayes (LB) factor is defined by Laplace(level): Laplace(diff).

Table 2b: Laplace-Bayes factor for six-variable BVARs using an informative prior

	Lag Length	λ_0	λ_1	λ_3	Log Laplace (level)	Log Laplace (diff)	LB factor
Productivity (CEV Hours)	3	.60	.118	.038	-1440.26	-1433.14	1243.89
Productivity (FR Hours)	3	.61	.106	.018	-1410.81	-1409.12	5.44
GDP per worker and Unemployment	2	.60	.103	.040	-1314.55	-1305.30	10331.98

Table 2c: Laplace-Bayes factor for six-variable BVARs using a diffuse prior

	Lag Length	λ_3	Log Laplace (level)	Log Laplace (diff)	LB factor
Productivity (CEV Hours)	3	.039	-2707.23	-2701.33	366.13
Productivity (FR Hours)	3	.016	-2678.76	-2677.61	3.16
GDP per worker and Unemployment	2	.040	-2168.20	-2159.85	4217.51

Table 3a: Confidence intervals for percentage of variance from technology for bivariate BVARs

Level specification

	Percentile	1 step	4 steps	8 steps	12 steps	20 steps	50 steps
Output	2.5%	.2079	.2332	.4216	.5884	.8025	.9845
	50%	.7637	.7894	.9061	.9510	.9862	.9999
	97.5%	.9977	.9983	.9996	.9998	.9999	1.000
Hours	2.5%	.0001	.0005	.0024	.0047	.0064	.0074
	50%	.0571	.1524	.2764	.3294	.3593	.3752
	97.5%	.4754	.6625	.7984	.8388	.8631	.8806

Difference specification:

	Percentile	1 step	4 steps	8 steps	12 steps	20 steps	50 steps
Output	2.5%	.0294	.0112	.0188	.0197	.0194	.0194
	50%	.2123	.1822	.2298	.2274	.2269	.2269
	97.5%	.4908	.4446	.5037	.5006	.5001	.5001
Hours	2.5%	.0069	.0001	.00	.00	.00	.00
	50%	.1440	.0250	.0176	.0178	.0179	.0179
	97.5%	.4117	.2244	.1866	.1872	.1884	.1884

Table 3b: Confidence intervals for percentage of variance from technology for six-variable productivity/CEV hours BVARs

	Percentile	1 step	4 steps	8 steps	12 steps	20 steps	50 steps
Output	2.5%	.0005	.0051	.0424	.0740	.2244	.7352
	50%	.1020	.2120	.4878	.6232	.8086	.9843
	97.5%	.4471	.5759	.8370	.9307	.9791	.9998
Hours	2.5%	.0001	.0002	.0004	.0016	.0148	.0409
	50%	.0535	.0645	.1228	.2365	.4943	.6950
	97.5%	.4429	.4733	.5754	.6907	.8590	.9731
Investment	2.5%	.0001	.0001	.0003	.0006	.0027	.1849
	50%	.0217	.0289	.1063	.1931	.3864	.9267
	97.5%	.2262	.2834	.5894	.7632	.8871	.9986
Inflation	2.5%	.1051	.1258	.1458	.1598	.1586	.1047
	50%	.5169	.5533	.5945	.6366	.7088	.7682
	97.5%	.8439	.8577	.8756	.8944	.9333	.9802
Federal Funds	2.5%	.0001	.0001	.0002	.0003	.0013	.0330
	50%	.0376	.0508	.0747	.1123	.2306	.5759
	97.5%	.3875	.4729	.5375	.5854	.6894	.9018
Trade deficit	2.5%	.0015	.0001	.0001	.0001	.0001	.0002
	50%	.0846	.0306	.0261	.0308	.0444	.0943
	97.5%	.2788	.2199	.2473	.3007	.4002	.6546

Table 3c: Confidence intervals for percentage of variance from technology for four-variable productivity/CEV hours BVARs

	Percentile	1 step	4 steps	8 steps	12 steps	20 steps	50 steps
Output	2.5%	.0002	.0016	.2247	.4869	.6511	.8968
	50%	.0607	.2037	.7579	.9071	.9628	.9968
	97.5%	.4233	.6155	.9510	.9917	.9986	.9999
Hours	2.5%	.0004	.0002	.0001	.0002	.0011	.0068
	50%	.1296	.0773	.0449	.0718	.2610	.5038
	97.5%	.6081	.5346	.4375	.5379	.7900	.9512
Inflation	2.5%	.0357	.0841	.0905	.0877	.0806	.0574
	50%	.5734	.6688	.6825	.6887	.6895	.6837
	97.5%	.9376	.9553	.9579	.9654	.9757	.9877
Federal Funds	2.5%	.0015	.0061	.0149	.0327	.0767	.1665
	50%	.1966	.3251	.4018	.4719	.5911	.7260
	97.5%	.6414	.7888	.8260	.8459	.8932	.9635

Table 4a: Conditional correlations corr(ε_{yt},Δy_{t-j}) of technology shocks for bivariate BVARs

Level specification

	Productivity			Hours		
Lag/Lead	Percentiles			Percentiles		
	2.5%	50%	97.5%	2.5%	50%	97.5%
-5	-.1187	-.0078	.1016	-.2051	-.0941	0.0423
-4	-.0537	-.0188	.0302	-.0221	.0466	0.1215
-3	-.1635	-.0558	.0517	-.0182	.1102	0.2314
-2	-.1101	.0127	.1349	-.0983	.0342	0.1632
-1	-.1395	-.0037	.1360	-.1248	.0138	0.1512
0	.5794	.9571	.9999	-.4983	.2363	0.8197
1	-.1350	.0014	.1421	-.1195	.0109	0.1399
2	-.0929	.0275	.1514	-.1284	-.0101	0.1091
3	-.1600	-.0296	.1192	-.1122	-.0131	0.0903
4	-.0531	-.0183	.0350	.0124	.0676	0.1147
5	-.1056	-.0082	.1286	-.1623	-.0842	0.0248

Difference specification

	Productivity			Hours		
Lag/Lead	Percentiles			Percentiles		
	2.5%	50%	97.5%	2.5%	50%	97.5%
-5	.0203	.0709	.1062	-.2401	-.1948	-.1375
-4	-.0800	-.0402	-.0087	-.0472	-.0059	0.0388
-3	-.1496	-.0505	.0526	.0115	.1181	0.2203
-2	-.0876	.0270	.1415	-.1014	.0184	0.1381
-1	-.1512	-.0141	.1249	-.1283	.0056	0.1399
0	.7861	.9266	.9935	-.6130	-.3685	-.1101
1	-.1469	-.0096	.1278	-.1314	.0024	0.1307
2	-.1072	.0121	.1333	-.1443	-.0319	0.0832
3	-.2089	-.1018	.0083	-.1295	-.0249	0.0848
4	-.0494	-.0259	.0026	-.0278	.0255	0.0773
5	.0178	.0807	.1501	-.2021	-.1669	-.1319

Table 4b: Conditional correlations corr(ε_{yt},Δy_{t-j}) of technology shocks for the four-variable BVARs

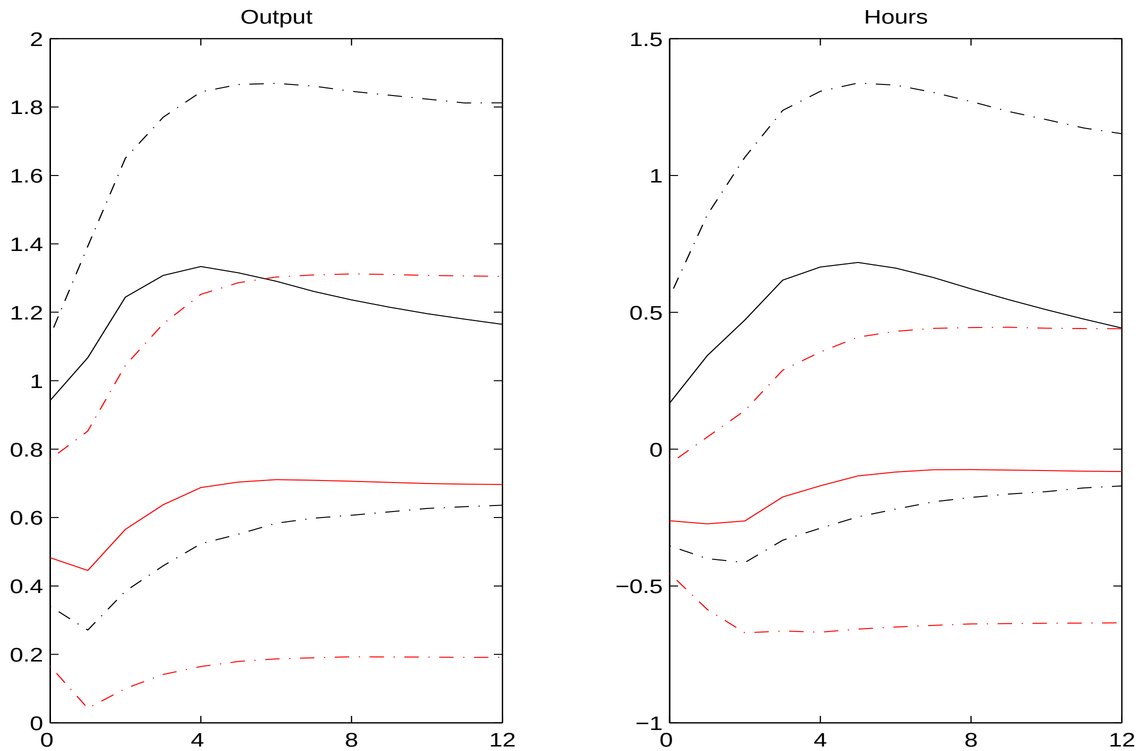
	Productivity			Hours			Inflation		
Lag/Lead	Percentiles			Percentiles			Percentiles		
	2.5%	50%	97.5%	2.5%	50%	97.5%	2.5%	50%	97.5%
-5	-.0062	.0673	.1313	-.2629	-.1411	-.0063	-.1577	-.0415	0.0790
-4	-.1032	-.0246	.0638	-.0690	.0317	0.1207	-.2051	-.1316	-.0305
-3	-.1471	-.0473	.0494	-.0535	.0541	0.1642	-.0272	.0874	0.1954
-2	-.1012	.0267	.1517	-.0646	.0710	0.1978	-.0779	.0474	0.1715
-1	-.1694	-.0486	.0758	-.1657	-.0412	0.0875	-.1026	.0547	0.2001
0	.2005	.5848	.8785	-.7725	-.3485	0.1985	-.9669	-.7582	-.1893
1	-.1403	-.0133	.1144	-.1675	-.0391	0.0858	-.0847	.0693	0.2040
2	-.1411	-.0244	.0916	-.1230	.0002	0.1206	-.1093	.0131	0.1400
3	-.2123	-.0977	.0266	-.0781	.0401	0.1531	-.0801	.0374	0.1376
4	-.0796	-.0014	.0837	-.1103	-.0214	0.0739	-.1727	-.0906	0.0325
5	-.0356	.0730	.1817	-.1793	-.1077	-.0277	-.1089	.0067	0.0915

Table 4c: Conditional correlations corr(ε_{yt},Δy_{t-j}) of technology shocks for the six-variable BVARs

	Productivity			Hours			Inflation		
Lag/Lead		Percentiles			Percentiles			Percentiles	
	2.5%	50%	97.5%	2.5%	50%	97.5%	2.5%	50%	97.5%
-5	-.0800	.0042	.0820	-.1776	-.0315	.1176	-.0813	.0656	0.1648
-4	-.0356	.0517	.1277	-.0371	.0703	0.1485	-.1874	-.1070	.0130
-3	-.0987	-.0102	.0728	-.0496	.0448	0.1419	-.0581	.0340	0.1258
-2	-.1043	.0143	.1428	-.0376	.0949	0.2085	-.0333	.0673	0.1634
-1	-.1107	-.0005	.1064	-.1280	-.0044	0.1182	-.0363	.1267	0.1634
0	-.1461	.3112	.7428	-.4885	.1313	0.6248	-.9182	-.7232	-.3538
1	-.1136	-.0050	.1268	-.1483	-.0234	0.1035	-.0508	.0909	0.2075
2	-.1277	-.0295	.0738	-.0486	.0810	0.1961	-.0528	.0877	0.2076
3	-.1485	-.0202	.1132	-.1669	-.0567	0.0559	-.0789	.0241	0.1131
4	-.1210	-.0522	.0301	-.1026	-.0171	0.0717	-.1959	-.1290	-.0327
5	-.0456	.0779	.1935	-.0875	.0506	.1566	-.1054	.0235	0.1131

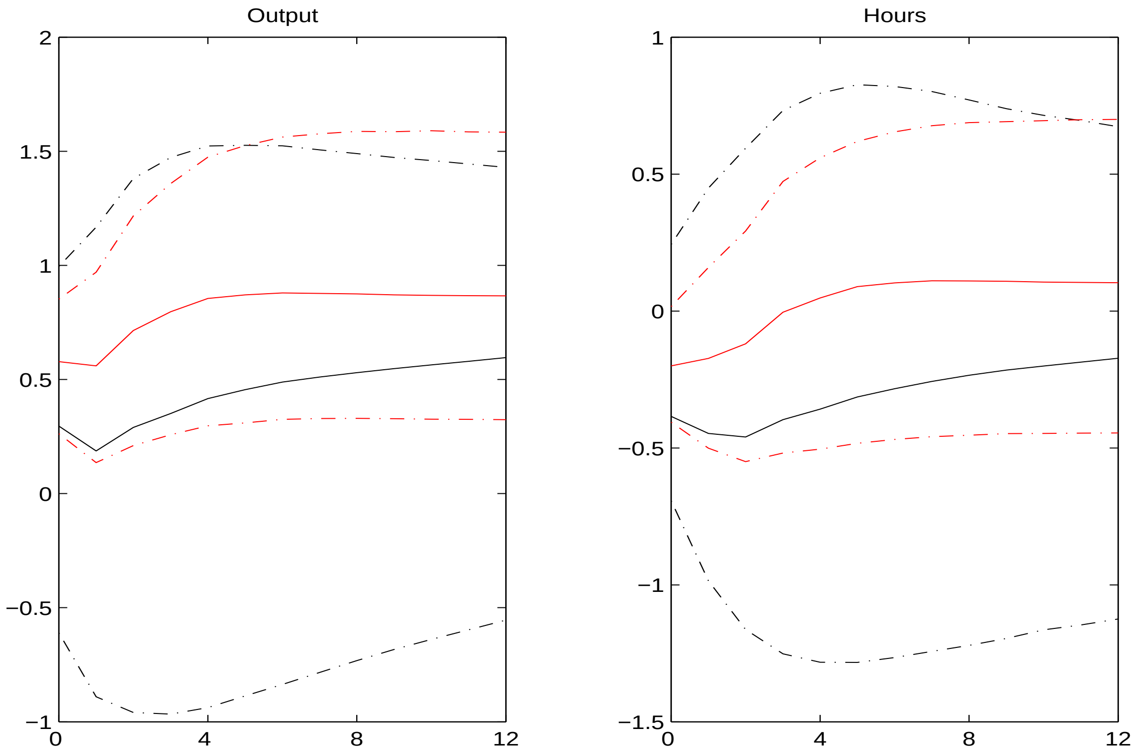
Figure 1: Measures of hours/employments (1959Q1-2004Q2)

Figure 2: Impulse responses functions from bivariate BVAR (productivity and CEV hours



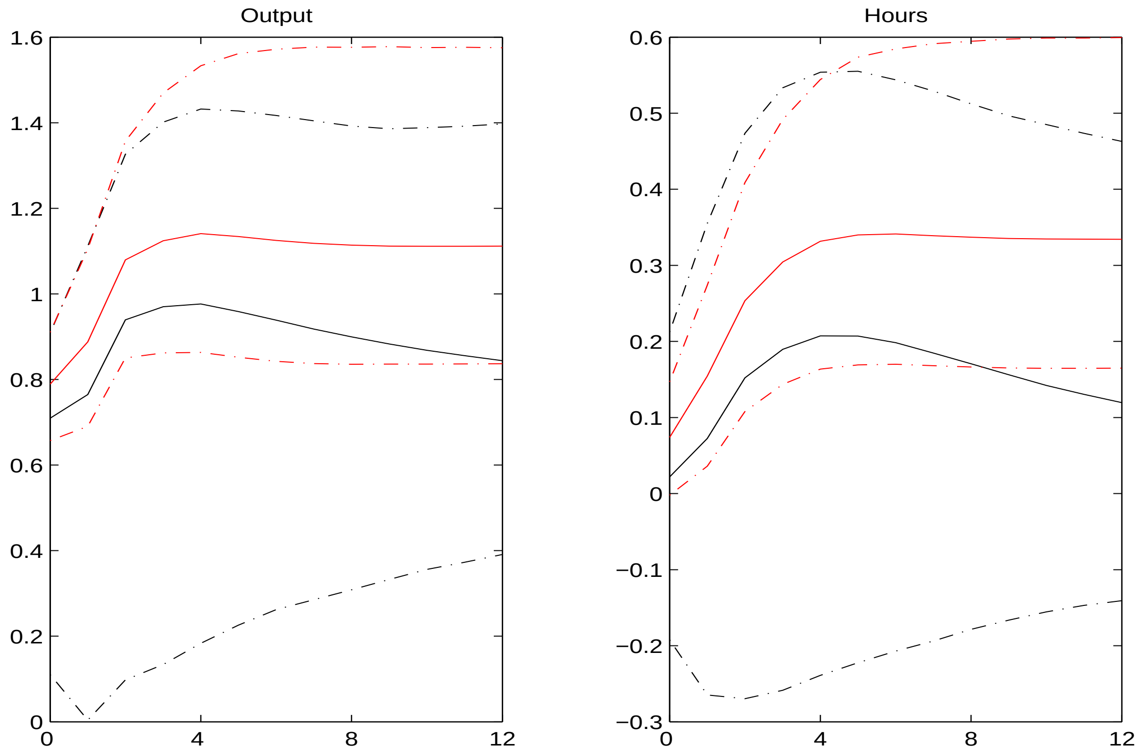
Note: IRFs from BVAR with hours in levels are black; those from the BVAR with hours in differences are in red. Solid lines indicate 50th percentiles; dotted lines are the bounds of 95% confidence bounds.

Figure 3: Impulse responses from bivariate VAR in productivity and FR hours



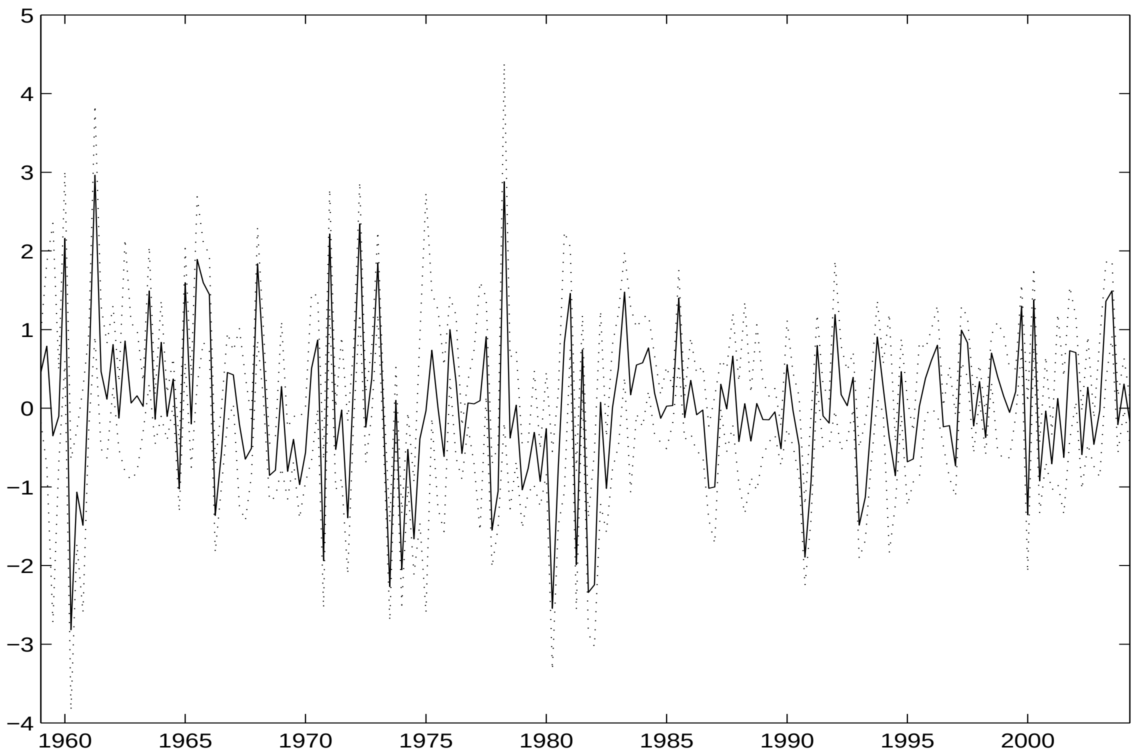
Note: IRFs from BVAR with hours in levels are black; those from the BVAR with hours in differences are in red. Solid lines indicate 50th percentiles; dashed lines are the bounds of 95% confidence bounds.

Figure 4: Impulse responses from bivariate VAR in GDP per worker and unemployment rate



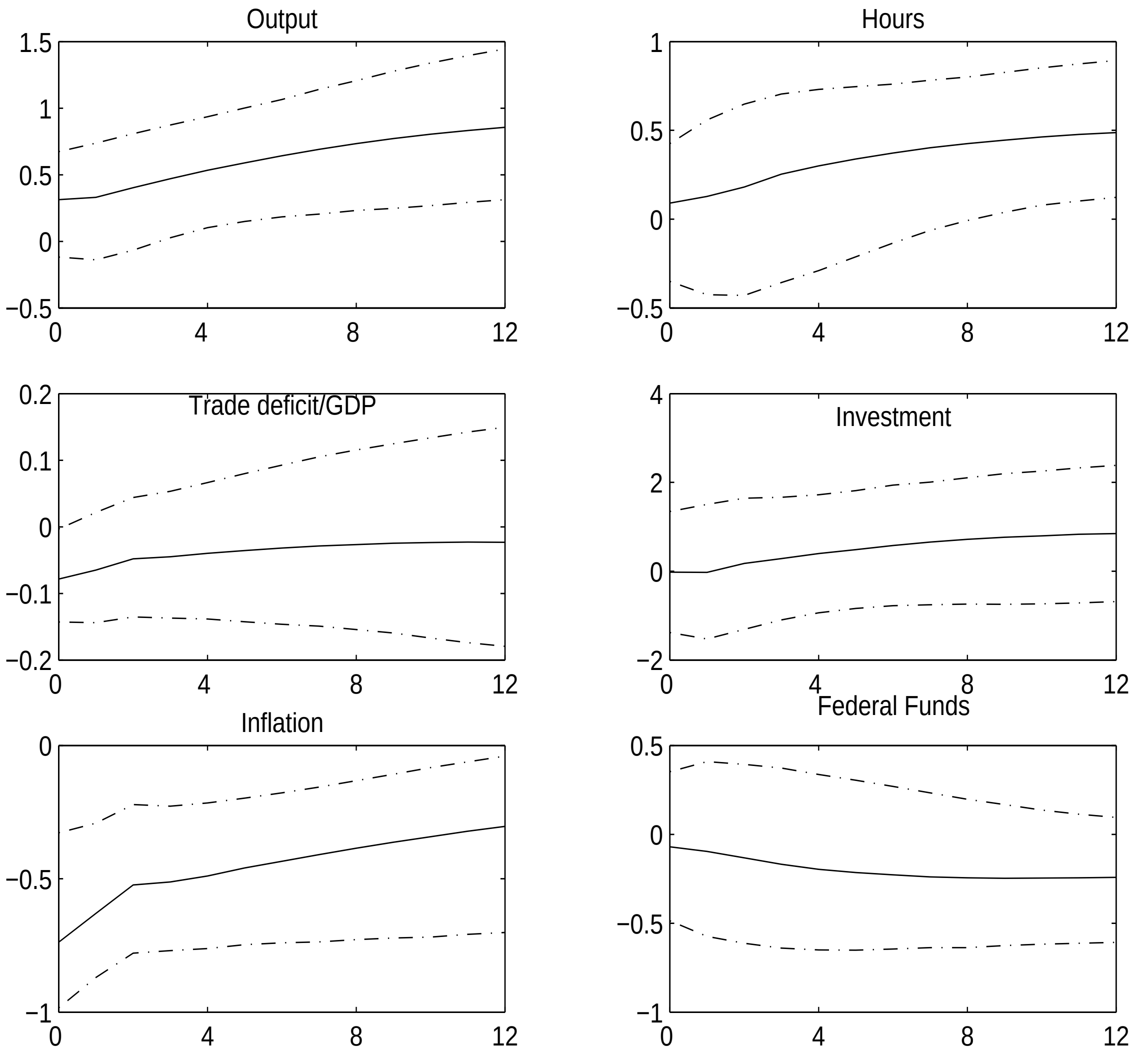
Note: IRFs from BVAR with hours in levels are black; those from the BVAR with hours in differences are in red. Solid lines indicate 50th percentiles; dashed lines are the bounds of 95% confidence bounds. Upward movement in "hours" here represents a fall in unemployment.

Figure 5: 95% confidence bands for identified technology shocks from bivariate BVAR in productivity and CEV hours.



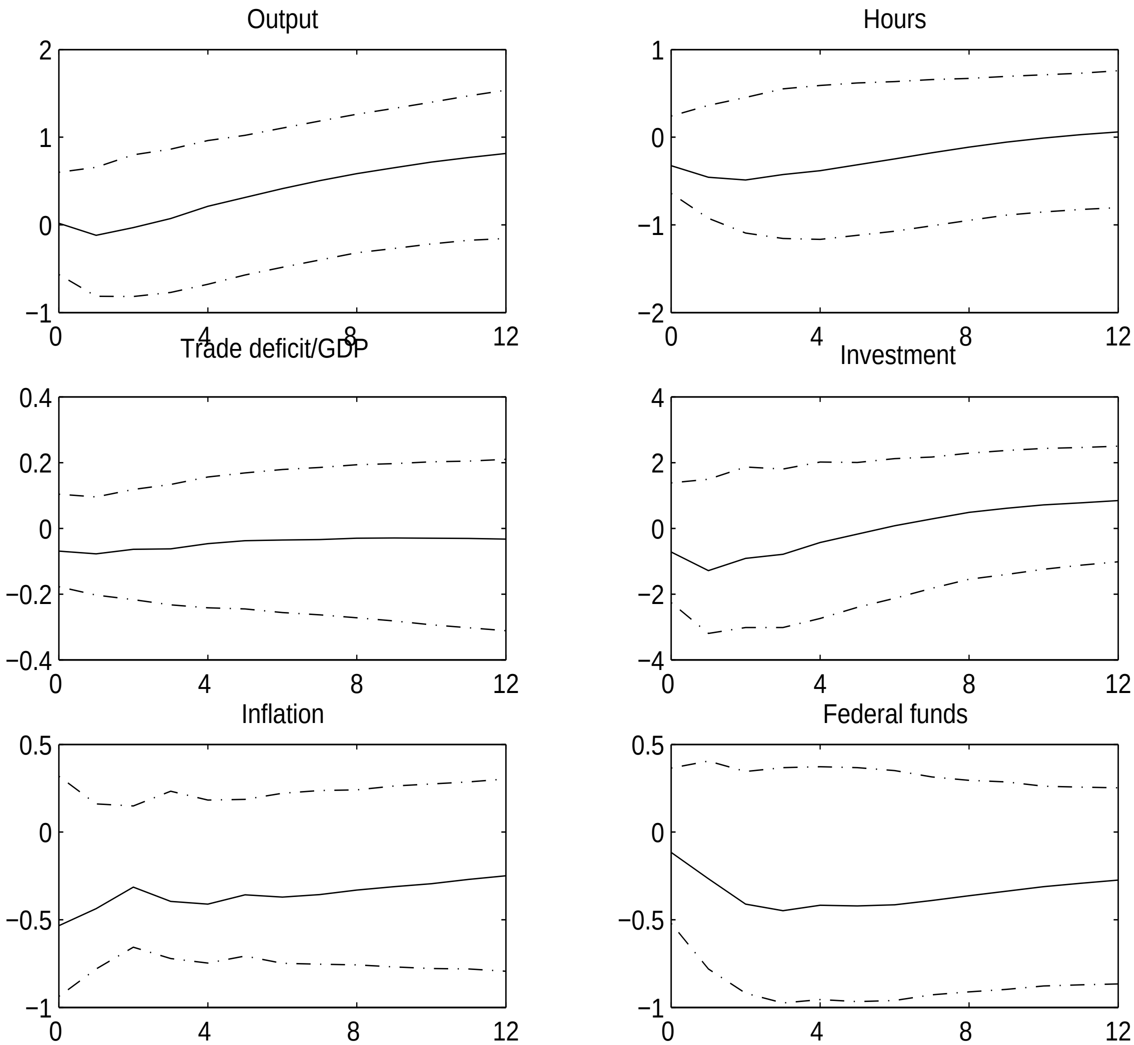
Note: Solid lines indicate 50th percentiles, with dotted lines indicating borders of 95% confidence bands.

Figure 6: Impulse responses from 6-variable VAR using productivity and CEV hours



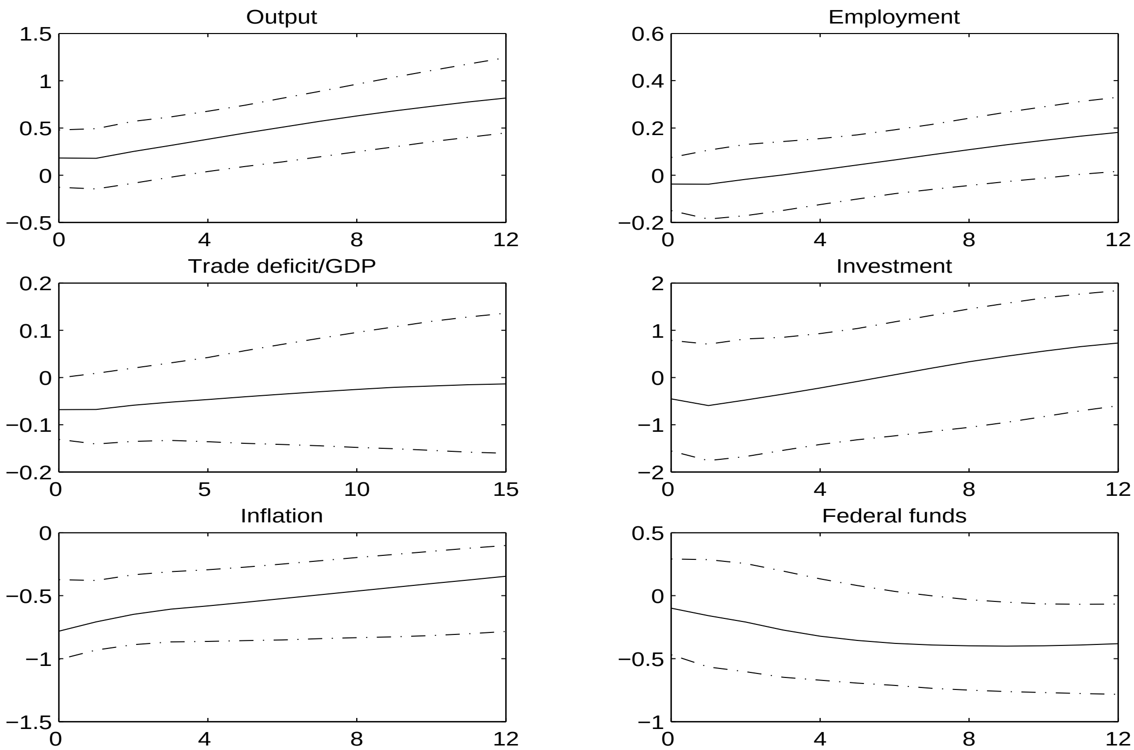
Note: Solid lines indicate 50th percentiles, with dashed lines indicating borders of 95% confidence bands.

Figure 7: Impulse responses from 6-variable VAR using productivity and FR hours



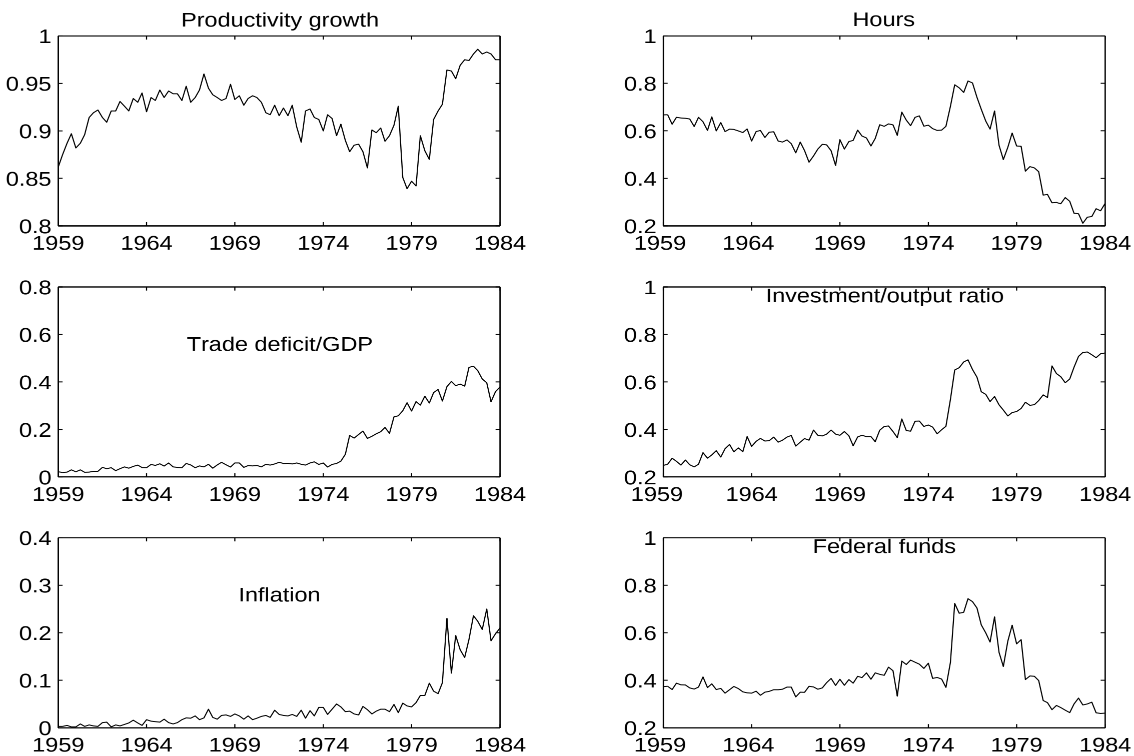
Note: Solid lines indicate 50th percentiles, with dashed lines indicating borders of 95% confidence bands.

Figure 8: Impulse responses from 6-variable VAR using GDP per worker and unemployment rate



Note: Solid lines indicate 50th percentiles, with dashed lines indicating borders of 95% confidence bands.

Figure 9: Posterior probabilities of positive effect from identified technology shock from shrinking regressions using six-variable VAR with productivity growth and CEV hours



Note: Solid lines indicate 50th percentiles, with dotted lines indicating borders of 95% confidence bands.

Figure 10: 95% confidence bands for identified technology shocks from four-variable BVAR with productivity and CEV hours.

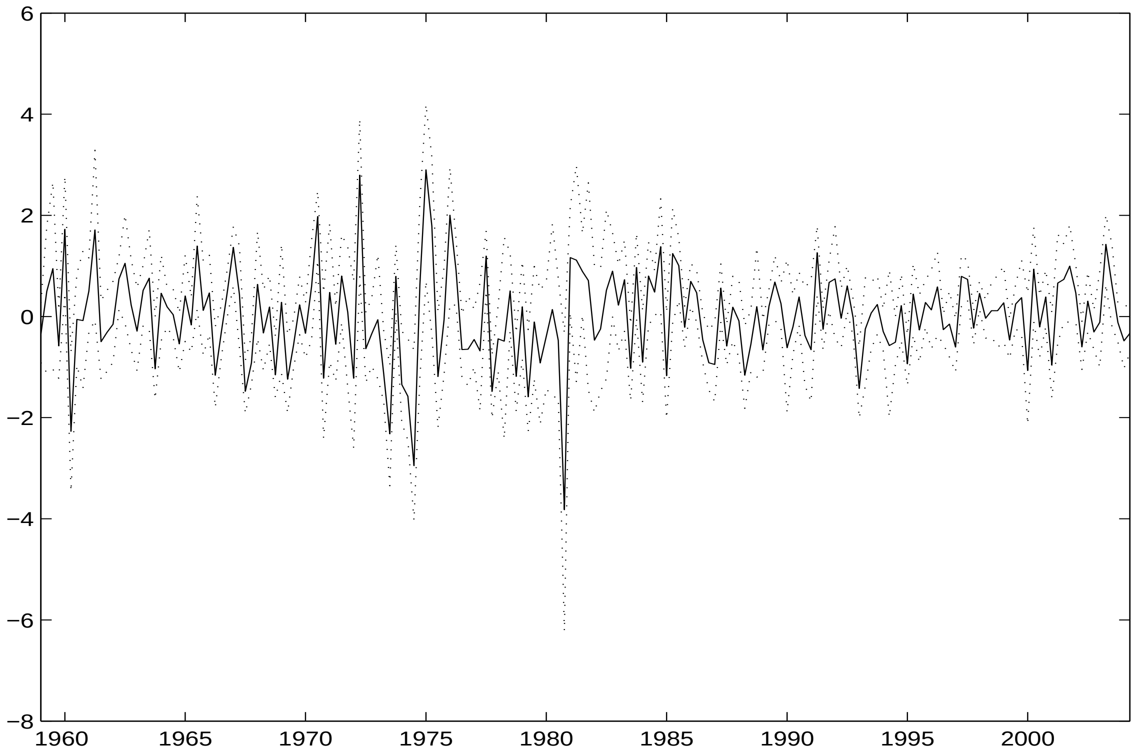
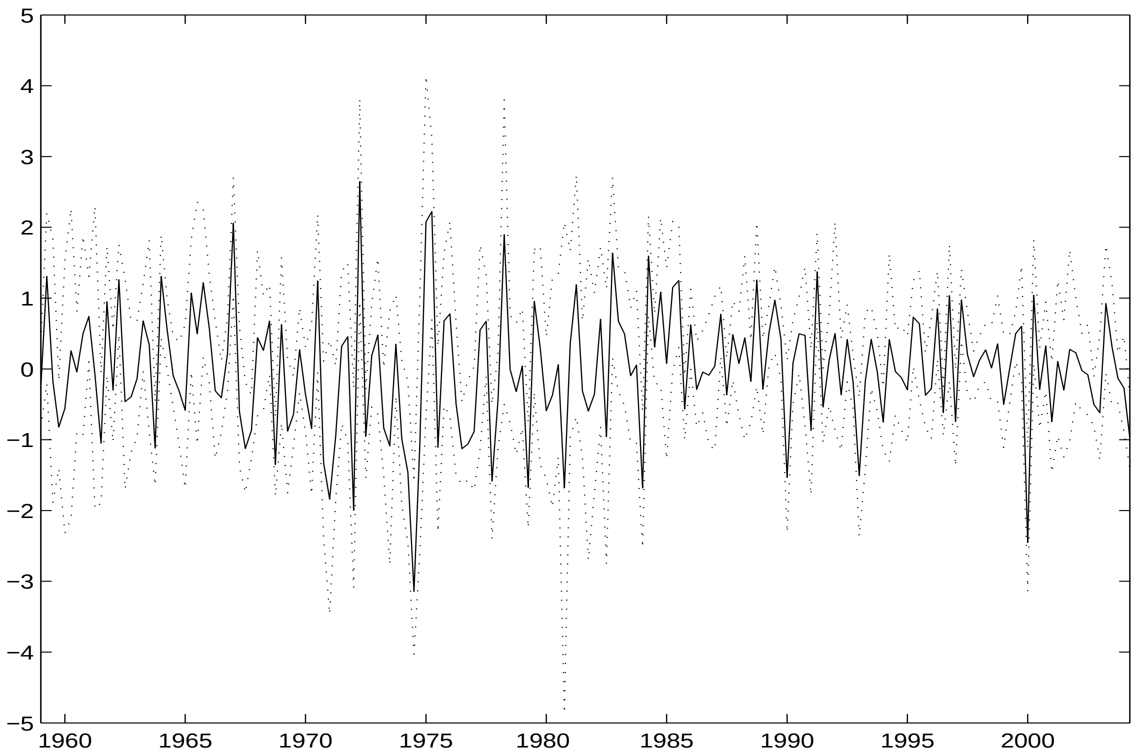


Figure 11: 95% confidence bands for identified technology shocks from six-variable BVAR with productivity and CEV hours.



Note: Solid lines indicate 50th percentiles, with dotted lines indicating borders of 95% confidence bands.

Figure 12: Impulse responses for 6 variable VAR estimated with productivity growth and CEV hours, with data from 1984:Q1 to 2004:Q2

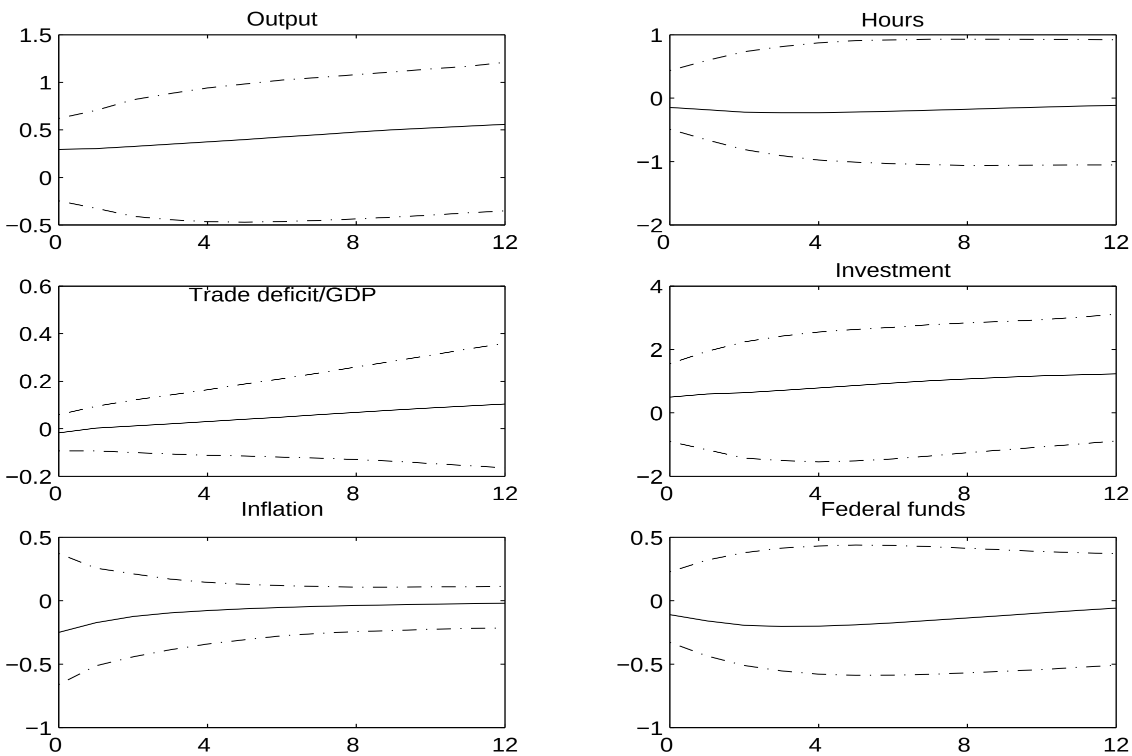


Figure 13: Posterior probabilities of positive effect from identified technology shock using an expanding window and a diffuse-Wishart prior

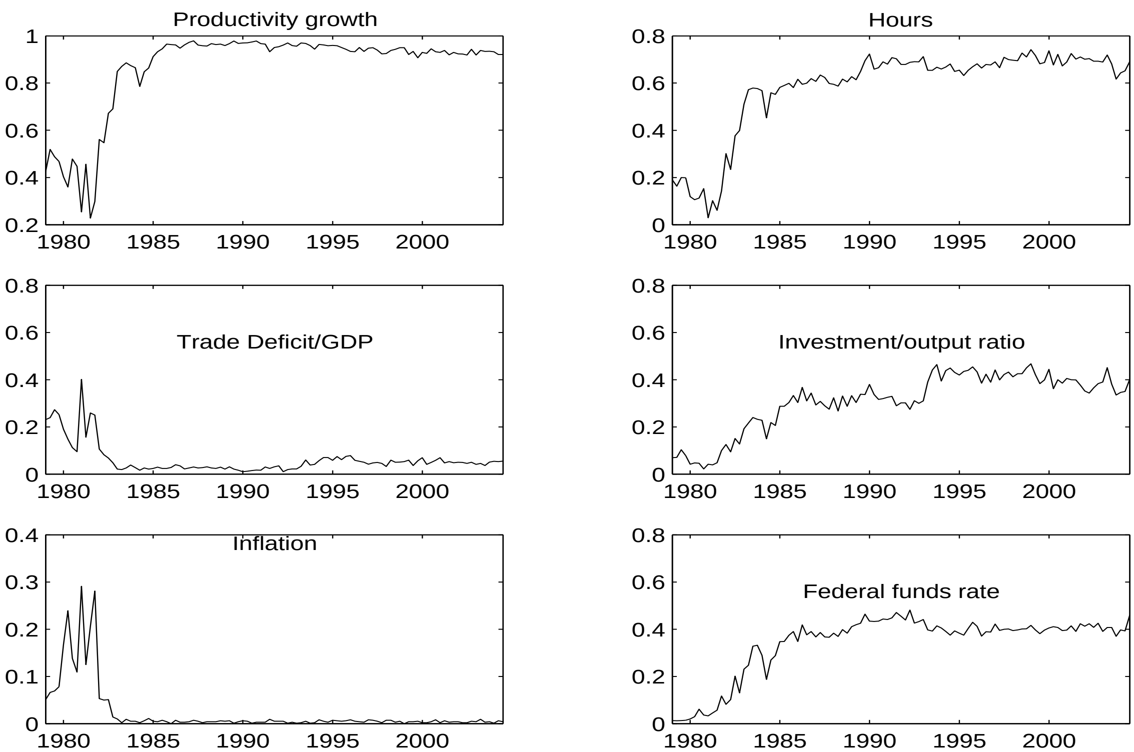


Figure 14: Posterior probabilities of positive effect from identified technology shock using a decreasing window and a diffuse-Wishart prior

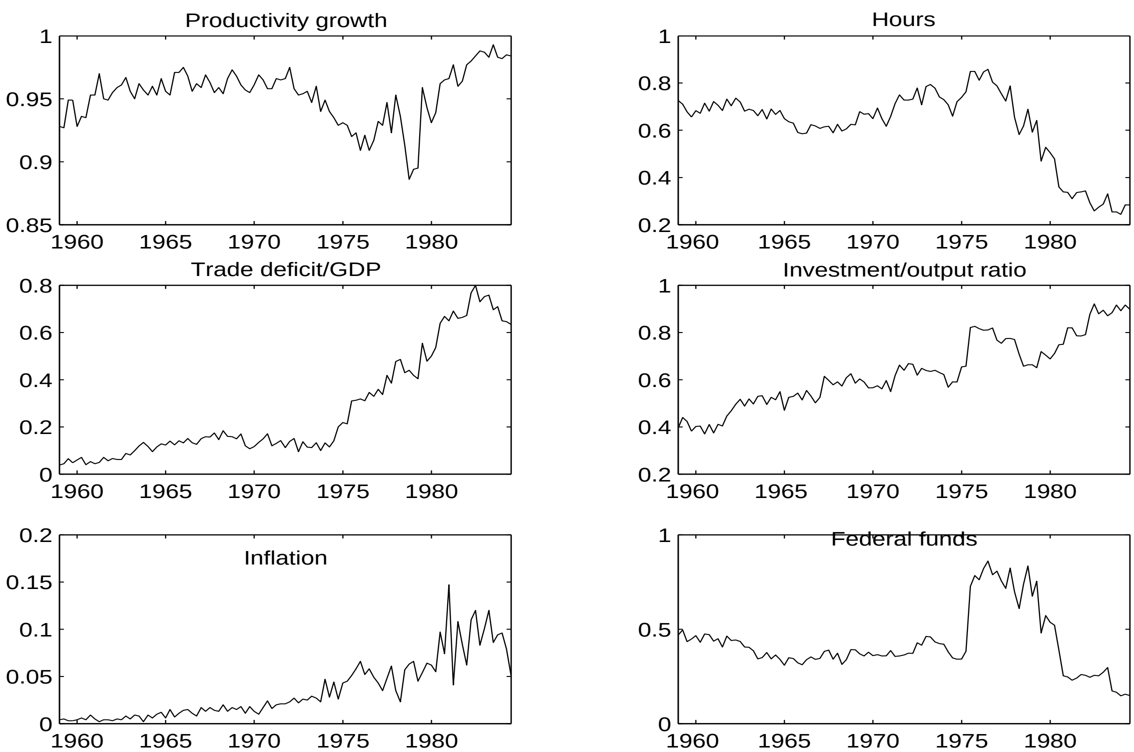


Figure 15: Robustness to a Normal diffuse prior