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Employment, Hours per Worker and the Business Cycle*

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Abstract

We examine the impact that technology shocks have in a trivariate VAR that includes productivity, hours worked per person and the employment ratio. These last two variables have trends that make them non-stationary. There are three results of interest. First, a technology shock reduces both hours and employment if those two variables are specified in first differences, with the response of employment being stronger than the response of hours. Second, a technology shock increases both hours and employment, when those two variables are specified in levels, although in this case the response of hours worked per person is stronger. Third, considering the possibility of changes in the trend growth rate of productivity reverses the results for the VARs with data in levels only. We also present a model that replicates some of the results for hours and employment.

Keywords: Business cycles, Employment, Hours worked, Technology shocks.

JEL Classification: E32

Resumen

Examinamos el impacto que las perturbaciones tecnológicas tienen sobre un VAR que incluye la productividad, horas trabajadas por persona y el empleo. Estas dos últimas variables tienen tendencias que las hacen ser no estacionarias. Obtenemos tres resultados de interés. Primero, una perturbación tecnológica reduce el número de horas y el empleo si estas dos variables están especificadas en primeras diferencias, siendo la respuesta del empleo mayor que el de las horas. Segundo, una perturbación tecnológica incrementa el número de horas y el empleo cuando estas dos variables están especificadas en niveles, siendo en este caso la respuesta del número de horas mayor. Tercero, cuando consideramos la posibilidad de cambios en la tendencia de crecimiento de la productividad, los resultados del VAR con datos en niveles se reverisan. También presentamos un modelo que replica algunos de los resultados para el número de horas y empleo.

Palabras Clave: Ciclos económicos, Empleo, Horas trabajadas, Perturbaciones tecnológicas.

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1 Introduction

How does a technology shock affect macroeconomic variables and in particular the labour market? According to the basic tenants of real business cycle models (RBC henceforth), exemplified by the work of Kydland and Prescott (1982) for example,¹ a positive technology shock should lead to increases in both the number of hours worked and output implying that there is a positive correlation between output and hours worked over the business cycle. As this correlation is observed in the US data, proponents of the RBC model conclude that such a model is able to explain the behaviour of major economic variables in the US (see for example King and Rebelo (1999)).

However, a number of recent papers (Galí (1999, 2004), Francis and Ramey (2004, 2005, FR henceforth) and Galí and Rabanal (2004)) have challenged this basic tenant using alternative tests that examine the impact technology shocks have on major macroeconomic variables. Unlike the tests reported by proponents of the RBC model - which usually evaluate the moments of macroeconomic variables - these papers employ tests which seek ‘to identify and estimate the empirical effects of exogenous changes in technology on different macroeconomic variables and to evaluate quantitatively the contribution of those changes to business cycle fluctuations’ (Galí and Rabanal (2004)). These tests (based on estimated VARs) yield results that are inconsistent with the basic RBC model since identified technology shocks tend to reduce the total number of hours worked. As this result contradicts the predictions of RBC models, these authors conclude that: first, technology shocks cannot be the main driving factors of the business cycle, and second, baseline RBC models must be missing important ingredients such as nominal or real inertia. These conclusions have prompted an active research agenda attempting to discern the sensitivity of these results to the various assumptions and data definitions used.

Christiano, Eichenbaum and Vigfusson (2003) (CEV henceforth) argue that Galí’s results are dependent on the definition of hours; once the correct definition is used an identified technology shock leads to an increase in hours. In response to this point, Galí and Rabanal (2004) examine twelve different measures for hours and argue that in eleven out of the twelve cases considered, an identified technology shock leads to a reduction in the number of hours worked with the twelfth case representing the data definition used by CEV. Moreover, in

¹By basic tenant we refer to an RBC model where all markets clear, there is no taxation, no government intervention, no monetary sector and no other imperfections.

that twelfth case the response of the labour input is very small and the identified technology shock only accounts for a small fraction of the variance of output and hours. FR (2005) test the identified technology shocks of Galí and CEV and find that Galí's identified technology shock provides a closer representation of the true technology shock than CEV's identified shock.

Behind these results lies an important statistical issue that appears to 'account' for all of these results. Galí, who uses total hours worked, argues that in the US data this variable has significant trends that render it non-stationary and that these trends must be removed to avoid spurious regressions. CEV argue that in a representative agent RBC model, the number of hours worked must be stationary in the long-run and therefore a much better proxy of the labour input is per capita total hours (which is closer to being stationary). Galí and Rabanal (2004) argue that when using CEV's measure, the response of hours per capita to an identified technology shock is not very statistically different from zero and that unit root tests of per capita hours suggest that this variable is not stationary. FR (2004) also take this issue. Their research considers alternative measures of total hours worked and in particular, possible explanations for why these data are trended. FR (2004) argue that positive trends in: (a) the share of employment in governmental jobs since the Second World War, (b) higher school and college student enrollment and (c) higher participation of those aged 65 and over in the labour market can all account for the nonstationarity in the data used by Galí and CEV. FR argue that once these three positive trends are taken into account, the resulting measure for total hours is stationary after the Second World War. Moreover, using these alternative series in both levels and first differences for the period since 1945 leads to the same conclusions reached by Galí (1999) and Galí and Rabanal (2004).²

Regardless of the measure of total hours worked used -where the debate has centered around -, it is important to note that the variables that make up total hours and total hours per capita have important trends that render them non-stationary: hours per worker and the employment ratio. This point was first made by Galí (2005) who shows that since the 1950s there is a clear positive trend in the total employment ratio, whereas hours worked per worker show a clear negative trend (standard RBC theory suggests both variables should be stationary). Moreover, the observed trend in total hours per capita appears to be driven

²In Appendix A we show these results. In only one case, where the measure of hours is consistent with CEV, does a technology shock lead to a statistically significant increase in the number of hours worked. Alternative transformations of total hours and hours per capita lead to either statistically insignificant responses of hours to the technology shock or to statistically significant decreases.

by the trend in the employment ratio, suggesting that (a) there may not be evidence of cointegration between the employment ratio and hours per worker and (b) modelling employment/unemployment is important to better understand the business cycle and in particular the behaviour of the labour market. Unfortunately, *standard* RBC models cannot explain these trends as they require a modification that incorporates decisions about total employment and hours worked per person. Nonetheless, in the last fifteen years we have seen attempts to model the employment and hours decisions of firms and households. For example, Andolfatto (1996) considers these decisions within the confines of a labour search model.³ He evaluates the performance of his model by comparing the moments implied by the model and those implied by the data, finding that the inclusion of unemployment can improve some of the predictions made by the standard RBC model. This conclusion is consistent with that one made by King and Rebelo regarding the explanatory power of RBC models. Andolfatto does not, however, test his model directly by examining the implications of identified technology shocks on the variables of interest. In this paper, we seek to test how an identified technology shock affects hours and employment and we compare results with a simple variant of the model proposed by Andolfatto. We discuss how the technology shock may be identified in a framework that comprises productivity, hours per worker and various measures of the employment ratio and evaluate the success of the model in matching the data. To our knowledge, there is no previous research that considers identification of technology shocks using these three variables jointly and therefore how these shocks affect employment and hours. An important by-product of our framework is that it allows us to examine whether it is hours worked per person, employment or both which explain the results in the papers by Galí, CEV and FR.

The outline of the paper is as follows: in section 2 we present some stylised facts regarding total hours, hours per worker and employment. Section 3 presents a variant of Andolfatto's model and discusses how the technology shock may be identified. Section 4 presents the empirical framework and conducts unit root tests on the variables of interest. Section 5 presents the main results of the paper. Section 6 presents an RBC model that is able to replicate some of the results found in Section 5. Section 7 concludes.

³Galí (1995) is another example of a model that introduces unemployment.

2 Trends in the US labour market

Figure 1 plots the measures of the labour input that have received so much attention: total hours and total hours per capita in the US.⁴ The source is the Bureau of Labor Statistics (BLS) and the period comprises 1964Q1 to 2004Q4.⁵ The figure shows that whilst there appears to be a positive trend in total hours, such trend cannot be observed clearly in the per capita series (that appear to be very persistent). Indeed, unit root tests suggest that total hours are non-stationary (p-value of 0.15) whereas total hours per capita exhibit a unit root at the 5% level and not at the 10% level (p-value of 0.08).⁶

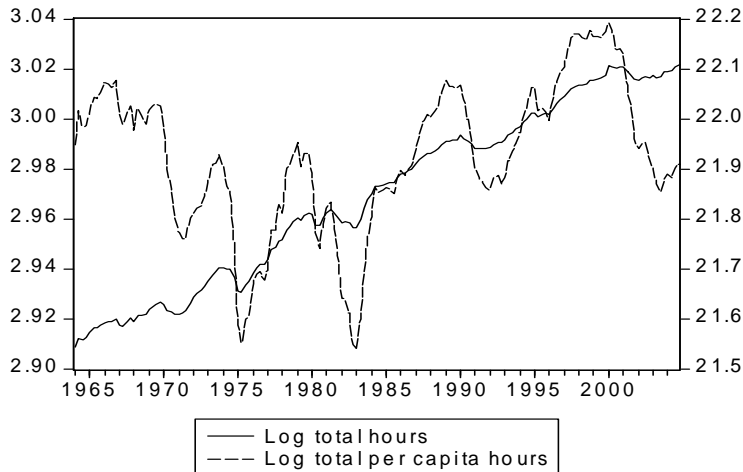


Figure 1: Total hours and total hours per capita

Figure 2 shows that the main driver behind the positive trend in total hours worked is the positive trend in total employment. Moreover, figure 2 also shows that the number of hours worked per worker (in the business sector) per week has a downward trend implying that the increase in total hours worked in the US economy is due to more employment rather

⁴Total hours are defined as the log of average weekly hours in the private sector times total employment. Total hours per capita is equal to the log of total hours divided by the population of age 16 to 64.

⁵The data were downloaded from the BLS's webpage: <http://www.bls.gov/ces/>.

⁶FR (2004) argue that positive trends in governmental employment may explain some of the positive trends in total hours. We followed their suggestions and adjusted these series by government employment. Such adjustment did not appear to change the (broad) conclusions regarding trends and persistence in these variables observed in figure 1: total hours continued to be non-stationary (p-value 0.17) whereas the p-value for the per capita series was 0.07. Results available on request.

than hours per person. Unit root tests confirm the significance of both trends: the p-values associated with unit root tests for these two variables are for hours person 0.29, and for total employment 1.00.

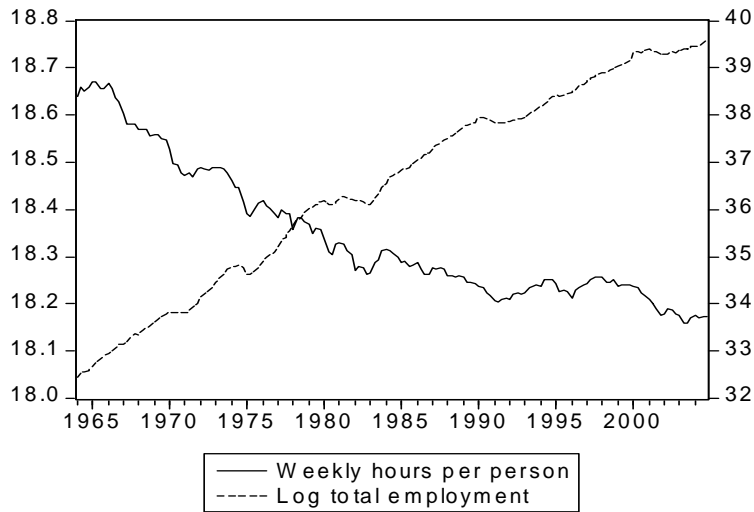


Figure 2: Hours worked per person and total employment

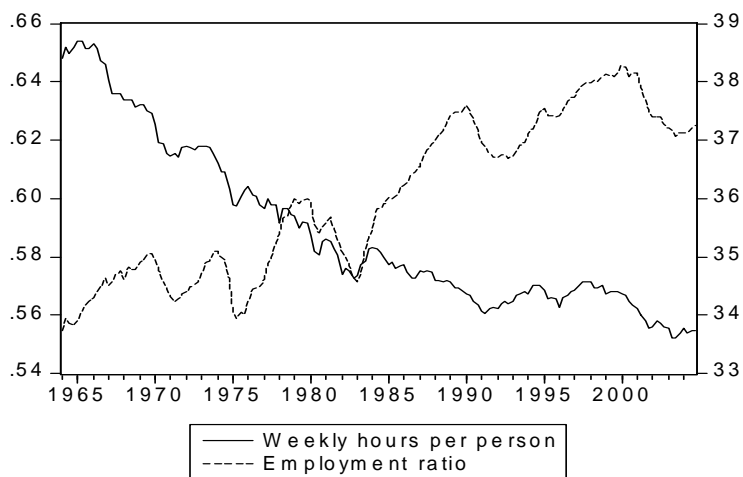


Figure 3: Hours per worker and the employment ratio

Figure 3 examines the sources of persistence in the total hours per capita measure that was plotted in figure 1. It appears that the peaks and troughs observed in the total number of hours worked per capita can be explained mainly by the employment ratio rather than hours per week. A unit root test with p-value of 0.1 suggests that these series have a slight positive trend.⁷

What is clear from these figures is that the behaviour of total hours and total per capita hours masks clear (and opposite) trends in weekly hours and in employment. Given that the number of hours worked per worker in the US is I(1), unless employment is of the same order of integration, and there is cointegration between these two variables, total hours worked will not be stationary (Galí’s conclusion). A number of questions arise. What drives the results found in Galí, CEV and FR? Is it hours per worker, employment or both? What statistical considerations must we take into account in order to identify technology shocks when using these three variables? Should we use variables in levels or in first differences in our VARs? Or could it be that the conclusions of Galí, CEV and FR change due to their use of total hours? We take up these issues in the remainder of the paper.

3 Technology shocks in a (simple) labour search model

We present a version of Andolfatto’s labour market search model which we shall use to identify the impact that technology shocks have on the labour market.⁸ A (benevolent) planner solves the following problem:

$$W(\tilde{\mathbf{S}}_t) = \max_{\tilde{C}_t, L_t, \tilde{\mathbf{S}}_{t+1}, V_t} E_t \sum_{i=0}^{\infty} \beta^i \left[\ln \tilde{C}_{t+i} + \frac{\phi_1 N_{t+i} (1-L_{t+i})^{1-\eta}}{1-\eta} + \frac{\phi_2 (1-N_{t+i}) (1-e)^{1-\eta}}{1-\eta} \right] \quad (1)$$

$$s.t. \tilde{K}_{t+1} = \frac{Z_t}{Z_{t+1}} \left(\tilde{Y}_t + (1-\delta) \tilde{K}_t - \tilde{C}_t - \kappa V_t \right) \quad (2)$$

$$\tilde{Y}_t = \tilde{K}_t^\theta (N_t L_t)^{1-\theta} \quad (3)$$

$$N_{t+1} = (1-\sigma) N_t + M_t \quad (4)$$

⁷Taking account of positive drifts in government sector’s employment did not dramatically change the observations made in figure 3. Total employment excluding the government sector renders it non-stationary (its p-value is now 0.5) but the measure of the employment ratio has a p-value of 0.08.

⁸We present the model of Andolfatto (1996) for at least two reasons: first, because it is claimed that “when labour market search is incorporated into a standard RBC model, the empirical performance improves along a several dimensions” (Andolfatto (1996) page 128). Second, because it permits us to examine how hours worked per person and employment should respond to a technology shock.

$$M_t = \chi_t V_t^\alpha ((1 - N_t) e)^{1-\alpha} \quad (5)$$

$$\tilde{\mathbf{S}}_t \equiv \left(\tilde{K}_t, N_t, Z_t \right) \quad (6)$$

plus the evolution of the technology shock Z . Y denotes output, C is consumption, L are hours spent working in the labour market, N is employment, e is effort (assumed to be constant), K is the capital stock, M is the matching function, V are vacancies and χ is a shock to the matching function that can be assumed to be stationary. ϕ_1 and ϕ_2 are preference parameters, κ is a parameter that measures the cost of posting a vacancy. The production function and the matching function take Cobb-Douglas forms. The \sim in consumption, output and capital denote that these variables have been scaled by the technology shock, ie $\tilde{C}_t = C_t/Z_t$ and so on. The first order conditions plus the laws of motion are:

$$\frac{1}{\tilde{C}_t} = \beta E_t \left[\frac{(1 - \delta) + \theta \frac{\tilde{Y}_{t+1}}{\tilde{K}_{t+1}}}{G_{Z,t+1} \tilde{C}_{t+1}} \right] \quad (7)$$

$$\phi_1 (1 - L_t)^{-\eta} = \frac{(1 - \theta) \left(\frac{\tilde{Y}_t}{N_t L_t} \right)}{\tilde{C}_t} \quad (8)$$

$$\frac{\alpha \kappa \chi_t V_t^{\alpha-1}}{\tilde{C}_t \beta ((1 - N_t) e)^{\alpha-1}} = E_t \left\{ \frac{\phi_1 (1 - L_{t+1})^{1-\eta} - \phi_2 (1 - e)^{1-\eta}}{1 - \eta} + \frac{(1 - \theta) \tilde{Y}_{t+1}}{\tilde{C}_{t+1} N_{t+1}} \right. \quad (9)$$

$$\left. + \frac{\kappa [(1 - \sigma) - (1 - \alpha) e^{1-\alpha} \chi_{t+1} V_{t+1}^\alpha (1 - N_{t+1})^{-\alpha}]}{\alpha \tilde{C}_{t+1} \chi_{t+1} \left(\frac{(1 - N_{t+1}) e}{V_{t+1}} \right)^{1-\alpha}} \right\} \quad (10)$$

$$\tilde{K}_{t+1} = \frac{1}{G_{Z,t+1}} \left[\tilde{K}_t^\theta (N_t L_t)^{1-\theta} + (1 - \delta) \tilde{K}_t - \tilde{C}_t - \kappa V_t \right] \quad (11)$$

$$N_{t+1} = (1 - \sigma) N_t + \chi_t V_t^\alpha ((1 - N_t) e)^{1-\alpha} \quad (12)$$

3.1 The steady-state of the model and long-run identification schemes

The steady-state of the model is:⁹

$$\text{MP capital/time preference link } \frac{G_Z}{\beta} = \theta \frac{\tilde{Y}}{\tilde{K}} + (1 - \delta) = \theta \left(\frac{NL}{\tilde{K}} \right)^{1-\theta} + (1 - \delta) \quad (14)$$

⁹The equation for the wage rate, which is not equal to the marginal product of labour, is obtained by assuming a decentralised economy:

$$W_t = (1 - \alpha) \left[(1 - \theta) \tilde{K}_t^\theta (N_t L_t)^{-\theta} + \frac{\kappa V_t}{(1 - N_t) L_t} \right] + \frac{\alpha \left[\phi_2 (1 - e)^{1-\eta} - \phi_1 (1 - L_t)^{1-\eta} \right] \tilde{C}_t}{(1 - \eta) L_t} \quad (13)$$

This equation demonstrates that in this model, the wage rate cannot be used as a proxy for productivity.

$$\text{Marginal rate of substitution } \tilde{C} = \frac{(1-\theta) \left(\frac{\tilde{Y}}{NL} \right)}{\phi_1 (1-L)^{-\eta}} \quad (15)$$

$$\text{Marginal value vacancies } V = \frac{\sigma\alpha\beta\tilde{C} \left\{ \frac{N\phi_1(1-L)^{1-\eta} - \phi_2(1-e)^{1-\eta}}{1-\eta} + (1-\theta) \frac{\tilde{Y}}{\tilde{C}} \right\}}{\kappa \left(1 - \frac{\beta[(1-\sigma)(1-N) - (1-\alpha)\sigma N]}{(1-N)\tilde{C}} \right)} \quad (16)$$

$$\text{Resource constraint } \frac{\tilde{C}}{\tilde{Y}} = 1 - \kappa \frac{V}{\tilde{Y}} + \frac{\tilde{K}}{\tilde{Y}} ((1-\delta) - G_Z) \quad (17)$$

$$\text{Vacancies } V = \left[\frac{\sigma N}{\chi ((1-N)e)^{1-\alpha}} \right]^{1/\alpha} \quad (18)$$

$$\text{Prod. function } \tilde{Y} = \tilde{K}^\theta (NL)^{1-\theta} \quad (19)$$

$$\text{MP of labour } \frac{\tilde{Y}}{NL} = (1-\theta) \left(\frac{NL}{\tilde{K}} \right)^{-\theta} \neq \text{Wage rate} \quad (20)$$

$$\text{Wage rate } \tilde{W} = \frac{(1-\alpha)}{L} \left[\frac{\tilde{Y}}{N} + \frac{\kappa V}{(1-N)} \right] \quad (21)$$

$$+ \frac{\alpha\tilde{C} [\phi_2 (1-e)^{1-\eta} - \phi_1 (1-L)^{1-\eta}]}{(1-\eta)L} \quad (22)$$

where G_Z denotes the growth rate of Z . Labour market rigidities (unemployment) do not affect the the marginal product of capital. This is the fundamental observation that allows us to identify the technology shock. Since unemployment, does not affect the equation for the marginal product of capital/time preference link the capital to output ratio is also unaffected. Thus labour productivity is not affected by unemployment. Unemployment, however, affects the wage rate breaking the link between this variable and the marginal product of labour (productivity). Thus productivity measures and wage rates are not equal suggesting that the wage rate should not be used to identify technology shocks.

Abstracting from taxation and other shocks, we examine how a (permanent¹⁰) technology shock affects the model's steady-state. This allows us to think about the identification of the technology shock using long-run restrictions in VARs. With a permanent technology shock, Y, C, K and W permanently increase ($\tilde{Y}, \tilde{C}, \tilde{K}$ and \tilde{W} are unaffected). Hours, employment and vacancies are not affected in the steady-state. Thus for the purpose of identifying a

¹⁰In this framework, it is assumed that the source of non-stationarity for output, consumption, capital stock, and real wages comes from the technology component. Thus it is assumed that technology shocks have a permanent impact on those variables that are non-stationary.

technology shock, in this model a permanent technology shock has permanent effects on the wage rate, labour productivity but not on hours, employment and vacancies.

Do any other variables have a permanent effect on labour productivity, wages, employment, hours or vacancies? Let's consider how χ affects the variables of interest (this will allow us to get a feel for the impact that non-technology shocks have in this model). Since this shock does not enter the MP capital/time preference link equation, $\left(\frac{NL}{K}\right)$ and thus labour productivity are not affected by this shock. Using similar arguments we see that other shocks (eg $\phi_1, \phi_2, e, \kappa$) will not affect productivity.¹¹ Finally, note that all these other shocks $\chi, \phi_1, \phi_2, e, \kappa$ will affect N, L , and V permanently.

Capital taxation may distort the identification of the technology shock as shown by FR. This is because in a basic RBC model taxes on capital affect the marginal product of capital:

$$\frac{G_Z}{\beta} = 1 + (1 - \tau_K) \left[\theta \frac{\tilde{Y}}{\tilde{K}} - \delta \right] \quad (23)$$

where τ_K is the rate of tax on capital income. No other tax variable enters this equation. Thus, both technology shocks and (permanent) capital taxation shocks affect the capital to output ratio, effective labour to capital ratio and productivity implying that capital taxes must be considered to ascertain whether they may affect identification of technology shocks.

3.2 Impulse responses in a log-linearised version of the model

We now examine how technology shocks affect the dynamics of the labour market variables of interest: employment and hours. This will allow us to evaluate the model's impulse responses against those obtained from our structural VARs that seek to identify the technology shock. In the analysis that follows we assume for simplicity that the technology shock evolves in log-linear form as:

$$z_t = \rho_z z_{t-1} + \varepsilon_t \quad (24)$$

The technology shock plus the rest of the model in log-linear form (denoted by lower case letters) yields expressions for c, y, r, k, n, l and v as well as the evolution of the exogenous shocks, z allowing us to consider the dynamic properties of our model. Figure 4 plots

¹¹The χ shock affects the vacancies condition and therefore the wage rate (which is also affected by $\phi_1, \phi_2, e, \kappa$). Thus the wage rate is affected by a variety of shocks and should not be used to identify technology shocks.

the impulse responses for employment and hours that result from a one percent shock to technology using the parameter values considered by Andolfatto, replicated here in Table 1.

β	θ	δ	η	ϕ_1	ϕ_2	e	G	L	N	α	σ	χ	κ	ρ_z
0.99	0.36	0.025	2	2.08	1.37	$L/2$	1.0015	$1/3$	0.57	0.6	0.15	2	0.105	0.95

Table 1: Parameter values

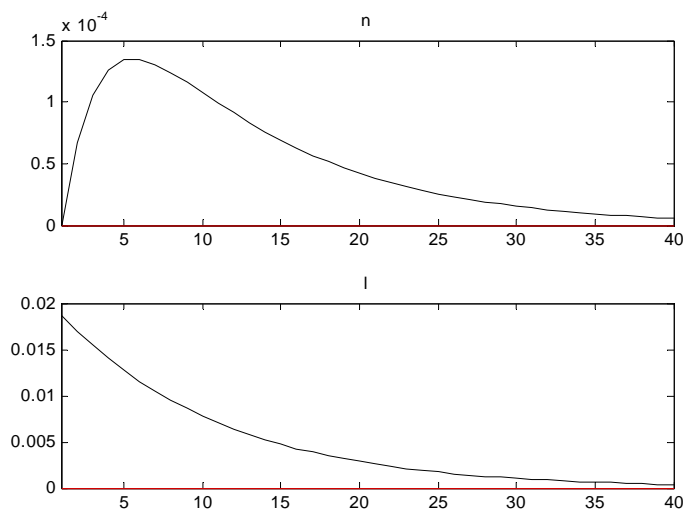


Figure 4: Effect of a technology shock on employment and hours

Following a positive technology shock both hours per person and employment increase (with the latter variable taking a little longer to increase and peaking after roughly six quarters). Total hours worked (the sum of log employment and log hours) also increases.¹²

¹²Output, consumption and capital all increase with consumption being smoother than output. When $\rho_z = 1$, after a one percent positive technology shock, output, consumption and the capital stock gradually increase to reach the technology shock. Hours, employment and total hours all return to their steady-state values implying that (permanent) changes in the technology shock do not have permanent effects on the labour variables.

4 Empirical framework

4.1 Identification

Galí (1999), CEV (2003) and FR (2005) consider identifying the technology shock within a bivariate model of labour productivity and hours:

$$\begin{bmatrix} \Delta p_t \\ h_t \end{bmatrix} = \begin{bmatrix} D^{11}(L) & D^{12}(L) \\ D^{21}(L) & D^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \epsilon_t \end{bmatrix} \quad (25)$$

where p_t denotes the log of labour productivity, h_t is the log of the labour input measure to use, ε_t is the technology shock and ϵ_t is a non-technology shock. $D^{ij}(L)$, $i, j = 1, 2$ denotes a polynomial in the lag operator. It is assumed that ε_t and ϵ_t are orthogonal. All the above papers identify the technology shock by imposing the restriction that $D^{12}(1) = 0$ (ensuring that the unit root in productivity originates entirely from the technology shock), differing in their assumption of the measure for the labour input. Galí uses Δh instead of h on the grounds that total hours are non-stationary. CEV use the level of h , where h denotes hours per capita. FR make adjustments to h to account for trends in government employment, college education and those of age 65+ that are not retired from the workforce. After making these adjustments, FR find that using h or Δh does not change their results; a technology shock has a negative impact on the number of hours worked. From a statistical point of view, this bivariate VAR requires only one restriction to identify the two structural shocks from the reduced form ones.¹³

Our framework is somewhat different since we have three variables: productivity, hours worked per person, l , and the employment ratio, n . Two issues of interest arise in our framework. The first issue relates to the identification of the technology shock whereas the second issue relates to the order of integration of the variables in the system given the observed trends in each of the variables. We take up the issue of identification first.

Our VAR is

$$\begin{bmatrix} \Delta p_t \\ l_t \\ n_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) & C^{13}(L) \\ C^{21}(L) & C^{22}(L) & C^{23}(L) \\ C^{31}(L) & C^{32}(L) & C^{33}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \epsilon_t^l \\ \epsilon_t^n \end{bmatrix} \quad (26)$$

¹³Imposing one further restriction would mean that this last restriction could be tested. This restriction could be that $D^{21}(1) = 0$ which is consistent with a basic RBC model (technology shocks should not affect hours in the long-run). In fact, of the three papers just mentioned only FR consider imposing the restriction that $D^{21}(1) = 0$ together with $D^{12}(1) = 0$ (although they do not impose this restriction in all of their VARs).

where all variables are in logs. $C^{ij}(L)$, $i, j = 1, 2, 3$ denotes a polynomial in the lag operator. All shocks are assumed to be orthogonal with ε_t denoting the technology shock and ε_t^k , $k = l, n$, the non-technology shocks. To identify each shock we must impose at least three restrictions on the $C(L)$ s. How can we identify the technology shock? Following the arguments presented in section 3.1 there is one obvious set of restrictions we can impose: we shall assume that only technology shocks have permanent effects on productivity implying that $C^{12}(1) = C^{13}(1) = 0$. This gives us two restrictions and so we need at least one more for the VAR to be just-identified. Nonetheless, note that these two restrictions allow us to fully identify the technology shock; the other two non-technology shocks require at least another restriction to be identified. We can consider a number of further restrictions. One of them is to assume that technology shocks do not have any long-run impact on hours nor employment implying that $C^{21}(1) = C^{31}(1) = 0$. These two further restrictions give a total of four restrictions implying that one of them is testable. Alternatively, we could consider other restrictions such as $C^{23}(1) = C^{32}(1) = 0$ implying that only the shock ε_t^k affects variable k , $k = l, n$. In the analysis that follows, we let the data speak by testing the various identifying restrictions for a variety of data definitions.

FR (2005) and Galí and Rabanal (2004) argue that capital taxation can be a potential difficulty for our identification scheme as this variable may contaminate our identification strategy (see section 3.1). To avoid this problem we use data for capital taxation in our VAR and follow FR by allowing capital taxation to enter the VAR as an exogenous variable (both contemporaneously and with a fourth quarter lag).

The second issue pertains to the order of integration of the variables of interest. We use quarterly data from 1964Q1 to 2004Q4 and our series are “Index of output per hours, business”, “total employment”, and “hours worked, business”.¹⁴ Unit root tests for the variables of interest are presented in table 2. The variable for employment, n , denotes the employment ratio, the variable presented in Andolfatto’s model.

Both variables of interest, n and l , appear to have trends that render them nonstationary. Thus, when these variables are used, one must make sure that they enter the VAR in first differences, or alternatively, if these variables enter the VAR in levels the residuals from such

¹⁴Valerie Ramey kindly provided us with the measure of capital taxes used in Francis and Ramey whose creator was Craig Burnside. Note that this sample is shorter than FR’s (their sample spans 1947Q1 to 2003Q1), the reason being that the series for the number of hours worked per person in the business sector starts in 1964Q1. The rest of the series of interest, productivity and the employment ratio, are available from 1947Q1. In Appendix B we examine whether the shorter data span may affect our results.

Variable	p-value
p	0.34
Δp	0
n	0.1
Δn	0
l	0.29
Δl	0
$n + l$	0.15
$ktax$	0.5
$\Delta ktax$	0

Table 2: Unit root test for variables of interest

VAR must be stationary. The capital tax rate series appear to be non-stationary. Finally and interestingly, the sum of log employment ratio and log hours per person (a proxy for total hours per capita) does appear to be non-stationary consistent with Galí's results.

5 Empirical results

In this section we consider a series of identification schemes for our VARs and examine whether the results change when capital taxation is included. Estimation of the VAR is undertaken with the following data possibilities: first, with the labour input series in first differences (termed Galí's VAR), and second, with the labour inputs in levels (termed CEV).^{15,16} The number of lags of the VAR are chosen according to various information criteria but subject to these residuals not being autocorrelated.¹⁷ All of the VARs passed tests for aforementioned autocorrelation and also for normality of the residuals. Before showing the impulse responses of interest, we first report a series of overidentifying restriction tests imposed on the reduced form VAR.

¹⁵We also considered VARs with the labour input using quadratic trends (this transformation is allowed for in FR). The results are similar to those obtained under the Galí estimation results. Since FR prefer the VAR with the labour input in first differences rather than without the quadratic trends we do not report those results here although they are available on request.

¹⁶We also considered a labour input series that accounted for the trends in government employment. Since the results did not change when we used these series, we do not report them although they are available on request.

¹⁷These required three lags for Galí's VAR and four lags for CEV's VAR.

5.1 Identifying restrictions and impulse responses for the structural VAR

Table 3 presents the results of imposing a number of overidentifying restrictions to the VAR of interest (restrictions $C^{12}(1) = C^{13}(1) = 0$ are already included).

Variables	Restrictions (these include $C^{12}(1) = C^{13}(1) = 0$)	p-value
Galí's VAR: First differences in n and l		
Δn and no capital tax	$C^{21}(1) = C^{31}(1) = C^{32}(1) = 0$	0.42
Δn with capital tax	$C^{21}(1) = C^{31}(1) = C^{32}(1) = 0$	0.44
CEV's VAR: Levels in n and l		
n and no capital tax	$C^{21}(1) = C^{31}(1) = C^{32}(1) = 0$	0
n with capital tax	$C^{21}(1) = C^{31}(1) = C^{32}(1) = 0$	0

Table 3: Overidentification tests

Thus the VARs with data in first differences satisfy a number of overidentifying restrictions; this is not true for the VAR with data in levels which is just-identified. Introducing capital taxation does not change the acceptance/rejection of these tests.

We turn next to the impulse responses associated with our identified VARs and examine how a technology shock affects productivity, hours and employment. Figures 5 and 6 each have two rows. Each row presents three diagrams with one impulse response each. The impulse responses represent the response of productivity, hours per worker and total employment to the identified technology shock. The second row in figures 5 and 6 presents the same results as the first row but includes capital taxation in the VAR.

5.1.1 Galí's VAR

Figure 5 presents the impulse responses for productivity, hours and employment following an identified technology shock using the identification restrictions reported in table 3. The standard error bands were computed using a bootstrap procedure with 1000 replications. We observe that the positive (identified) technology shock has a positive impact on productivity and a negative impact on employment and hours (although for this last variable this is somewhat inconclusive due to the large confidence intervals). The figure also shows that the introduction of capital taxation does not change the results. Of interest is the observation that employment appears to respond more to a technology shock than hours. These results

appear to be consistent with those found in Galí (1999) and FR (2005).

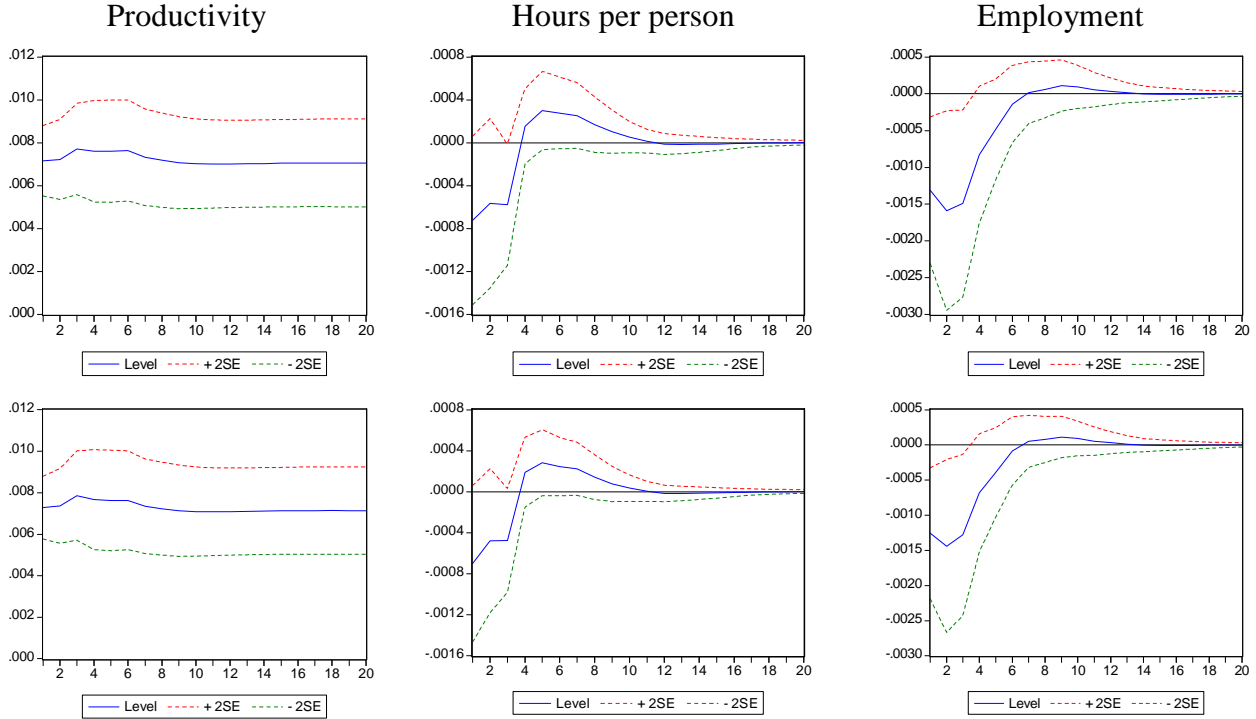


Figure 5: Effect of technology shock on productivity, hours and employment

5.1.2 CEV's VAR

Figure 6 reports the equivalent impulse responses to figure 5 when employment and hours enter in levels and not in first differences. Following a positive (identified) technology shock, productivity, hours and employment all increase (although the results for the labour market variables are mostly inconclusive due to the large confidence intervals). These results are (roughly) consistent with CEV's results and with the RBC model presented in section 3. Nonetheless, there are two important observations that appear to be inconsistent with the model presented in section 3: first, hours per person continue to be positive after 20 periods and never return to zero (this restriction is not satisfied by the data); and second, the standard error bands are wide and in particular do not exclude the possibility that employment

could fall following a technology shock. The introduction of the capital tax variable does not seem to change the results although it appears to improve the results for hours per person.

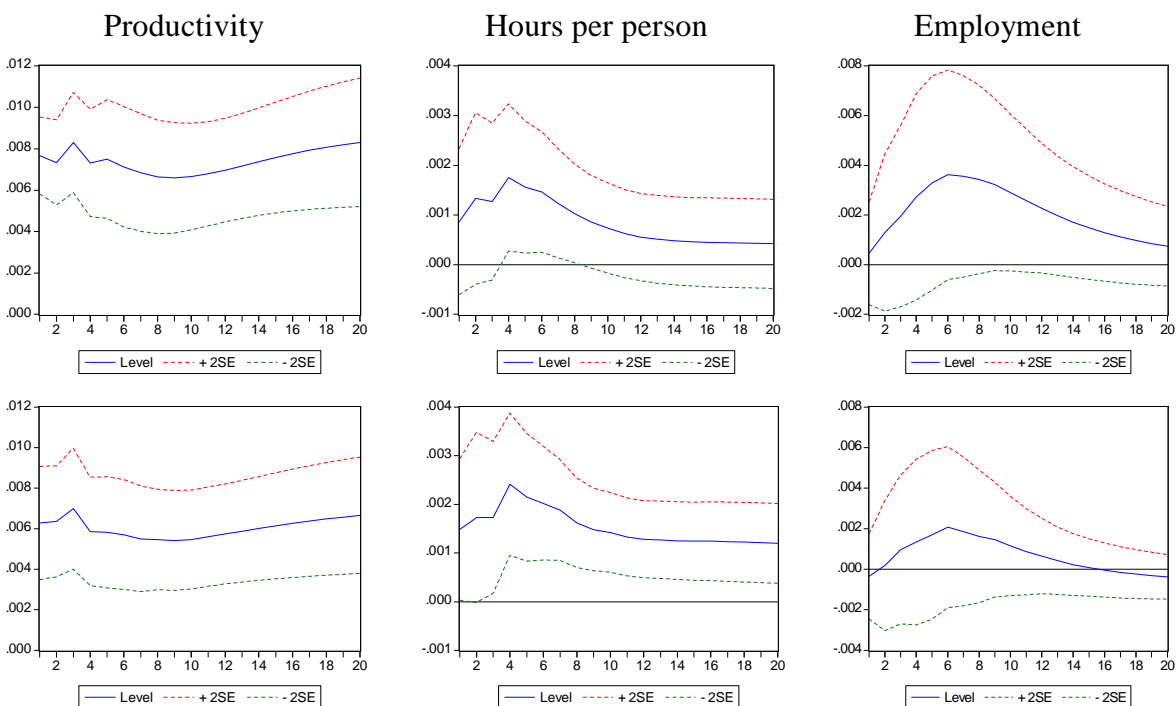


Figure 6: Effect of technology shock on productivity, hours and employment

5.2 Which VAR best identifies the technology shock?

There appears to be two conflicting views for the impact that technology shocks have on the labour inputs: the VAR in levels suggests that a positive technology shock increases hours and employment (a view consistent with standard RBC models), whereas the VARs with stationary variables suggest that hours and employment fall (a view that is inconsistent). If the VAR which uses stationary data correctly identifies the technology shock, we would conclude as Galí and FR before us, that technology shocks are not able to explain the business cycle. If on the other hand, the VAR in levels correctly identifies the technology shock, then standard RBC models should continue to be used as building blocks for understanding the

business cycle. Thus it is important to ascertain which of the VARs better identifies the technology shock.¹⁸

To answer this question we follow FR (2005) and Galí and Rabanal (2004) by undertaking two types of tests. First, we test whether the technology shock is correlated with other exogenous shocks that should not, in principle, be correlated with technology. Second, we examine whether our identified technology shocks can explain the behaviour of the technology measure constructed by Basu, Fernald and Kimball (2004).¹⁹

5.2.1 The effect of non-technology variables on the identified technology shocks

To examine whether the identified technology shocks are truly exogenous with respect to known non-technology shocks, we regress these identified shocks on a number of measures that should be uncorrelated with technology and which have been used elsewhere in the literature. These measures are: the Fed’s fund rate (Bernanke and Blinder (1992)), dummies for periods of military build-ups (Ramey and Shapiro (1998)), and the change in the price of oil (Hoover and Perez (1994)). Figure 7 plots these last two variables.

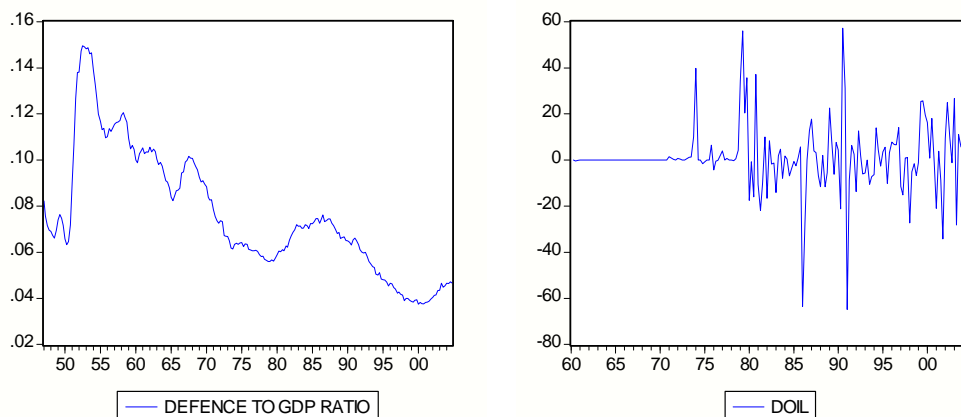


Figure 7: Non-technology shock variables

¹⁸In further exercises, we applied linear and quadratic trends as well as an HP filter to the data that entered the VARs in levels (ie CEV’s VARs). When these data were included, the responses of hours per person and employment were either not statistically significant or negative, consistent with the results of estimating VARs in stationary form.

¹⁹Note that in the results that follow, and to avoid producing a large number of charts and tables, we only present results for the VARs that did not include capital taxation. None of the results changed when alternative VARs with different employment measures and capital taxation were considered.

Following Ramey and Shapiro (1998) we identify as war date dummies the following periods: 1965:1 (the Vietnam war) and 1980:1 (the Carter-Reagan Build-up following the Soviet invasion of Afghanistan). To these two dates we also add the recent military build-up following September 11th 2001 which resulted in military actions in Afghanistan and Iraq (see the reversal of the downward trend in figure 7). Thus, following Ramey and Shapiro (1998) we create a dummy variable with the dates 1965:1, 1980:1 and 2001:4 (the start of conflicts in Afghanistan and elsewhere).

Table 4 shows whether current and fourth lagged values of the war dummy, current and fourth lagged values of the change in the oil price and the first and fourth lag of the interest rate variable have any predictive power for the identified technology and non-technology shocks that were derived from the VARs estimated in section 5.2. The p-values represent the probability of accepting the null hypothesis that all regressors are jointly insignificant.

Shocks	Ramey-Shapiro War date	Hoover-Perez oil dates	Fed funds rate
Galí VAR			
Technology shock	0.16	0.13	0.12
Non-technology shock hours	0.77	0.42	0.13
Non-technology shock employment	0.97	0.02	0.04
CEV VAR			
Technology shock	0.1	0.17	0.0
Non-technology shock hours	0.98	0.18	0.97
Non-technology shock employment	0.59	0.06	0.2

Table 4: P-values for exogeneity tests based on F-tests for significance of all regressors

Examining first Galí's VAR, we see that the identified technology shock appears to be orthogonal to all three shocks. This conclusion cannot be applied to CEV's VAR: the Fed funds rate has predictive power for the technology shock (and the war dates variable has predictive power at the 10% level). Turning now to whether these exogenous (non-technological) shocks can explain the identified non-technology shocks, we see that the shocks associated with hours cannot be explained by any of these variables. The war dates dummy is also unable to explain any of the non-technology shocks associated with employment. However, the oil dates variable has predictive power on all of the non-technology shocks associated with employment, whereas the Fed funds rate only has predictive power for employment in

Galí's VARs.²⁰

5.2.2 Can an alternative proxy (Basu, Fernald and Kimball's) for technology shocks be explained by our technology shocks?

As a test for the validity of their identified technology shocks, Galí and Rabanal (2004) make use of the measure of aggregate technological change of Basu, Fernald and Kimball (2004), BFK henceforth. BFK constructed that series by controlling for non-technological effects in aggregate total factor productivity (such as varying utilisation of capital and labour, non-constant returns and imperfect competition and aggregation effects) using growth accounting methods in industry level data. Galí and Rabanal assess the plausibility of their (VAR) identified technology shocks by examining the correlations between their identified shocks (both technological and non-technological) and the technology series constructed by BFK. Running a regression of the BFK series on its own lag, and the two identified shocks (one technological and one non-technological), they argue that the statistically significant coefficient on their technology shock, and the statistically insignificant coefficient in their non-technology shock in their regression suggest correct identification. We employ this test on our identified shocks. In the results that follow, we present regressions of the BFK measure on the identified technology shock and the sum of the non-technology shocks (the lagged values of the BFK measure were not significant in any of our regressions). The results were (t-stats in brackets) for the period 1966 to 1996:

$$\begin{aligned}
 BFK_t &= \underset{(2.27)}{0.01}tech_t^{Galí} + \underset{(0.9)}{0.003}nontech_t^{Galí} \\
 BFK_t &= \underset{(1.87)}{0.01}tech_t^{CEV} - \underset{(-1.41)}{0.005}nontech_t^{CEV}
 \end{aligned}$$

thus according to these regressions, one would probably favour the technology shock arising from Galí's VAR compared to the shock arising from CEV's VAR since the identified VAR technology shocks appear to be less significant there.

Considering the results reported in sections 5.2.1 and 5.2.2, we would tentatively conclude that it is Galí's VAR which appears to come closest to identifying the technology shock.

²⁰However, one should not put too much weight on the results for the non-technology shocks on the grounds that these were probably not very well identified.

5.3 Some sensitivity analysis: the impact of productivity trend breaks and an alternative identification scheme using sign restrictions

We now investigate whether any of the previously reported results change if we consider transformations to the measures of productivity or alternative identification schemes in the VARs of interest.

5.3.1 Productivity trend breaks

In a recent paper, Fernald (2005) shows that once US productivity is corrected for trend breaks, the response of hours to a technology shock is negative regardless of whether hours enter in levels or in first differences. We consider whether this proposition changes any of our previous results. We only report the results that exclude capital taxation (using different measures for n and including capital taxation did not change the results).

Following Fernald, we create two alternative measures for productivity. These two specifications are proposed on the observation that unit root tests with structural breaks suggest that the behaviour of productivity is different during the period 1973Q2 to 1997Q1 than over the rest of the sample, 1947Q1-2003Q4. These two measures are obtained by running a regression of the productivity shock on a constant and for one of the specifications on a dummy which is equal to one prior to 1973Q1 and zero thereafter and for the other specification on two dummies, one which is the previously mentioned one plus another dummy that is equal to zero prior to 1997Q2 and one thereafter.

Figure 8 “replicates” the results of Fernald for our sample. It shows the response of hours to the identified technology shock for three cases: first for the case where different trend rates of productivity are not accounted for (baseline case), second, for the case where there is a different trend in the pre-1973 period compared to the post 1973 period and third where there is a different trend in the period 1973 to 1997. The first row shows the results commonly found in the literature (Galí and CEV respectively), the second row presents the results of our pre-1973 productivity measure and the third row presents the results of our pre-1973 and post-1997 productivity measure. The first column uses variables in first differences, whilst the second column uses variables in levels.

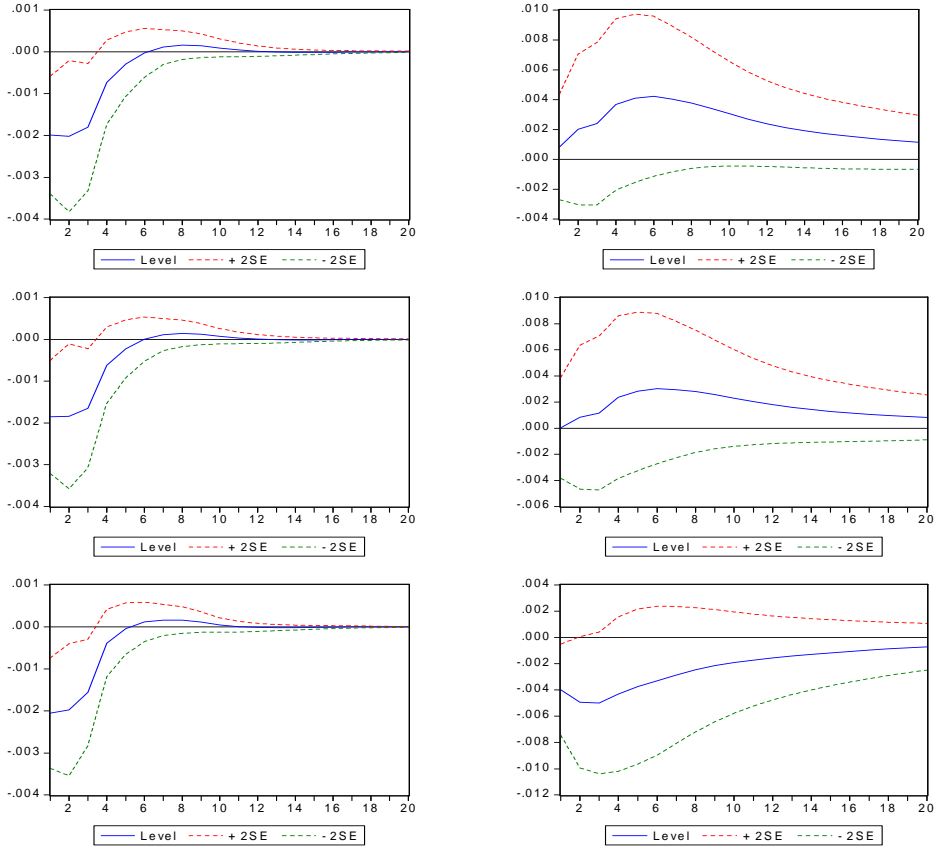


Figure 8: Effect of trend breaks on total hours

The results are similar to those in Fernald although our confidence bands are larger specially for the data in levels. This is a problem of the sample period, for this problem is not reported when we used the data kindly provided by Francis and Ramey which extended to 1947.²¹ The results suggest that the different productivity measures do not change the results of Galí's VARs but can have drastic effects for the VARs estimated in levels; CEV's VARs. In fact, for the last VAR, the impact of technology shock on hours is negative on impact.

Figures 9 and 10 show how hours per worker and employment respond to the different measures of productivity. As in figure 8, the first column represents the variables in first

²¹This of course suggests potential instability in the estimated coefficients of the VAR, as found by Fernald (2005).

differences, whilst the second column represents the variables in levels. The rows are also consistent with the descriptions used for figure 8 with respect to the productivity variable used.

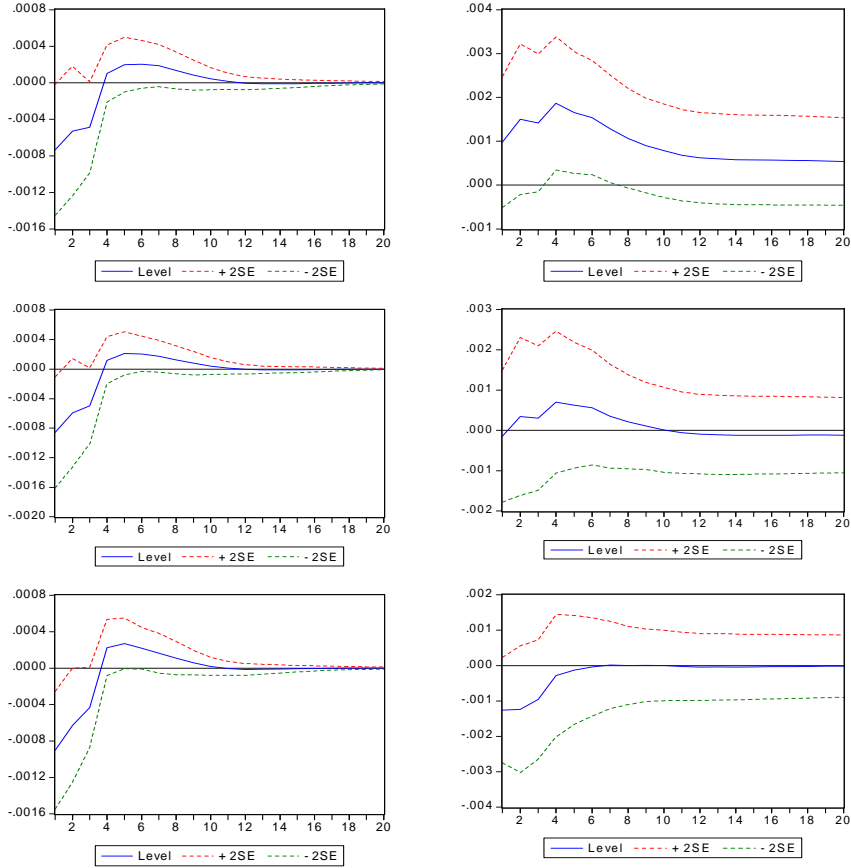


Figure 9: Response of hours per worker to different productivity measures

Figure 9 shows that once we allow for differences in the productivity measure, there are no marked differences for the specifications in first differences; if anything we can now say that for the last VAR, statistically, hours worked per person fall following a technology shock. For the case of the VAR in levels, we observe that the impulse responses plus confidence intervals appear to shift from positive to negative, albeit statistically insignificant, territory.

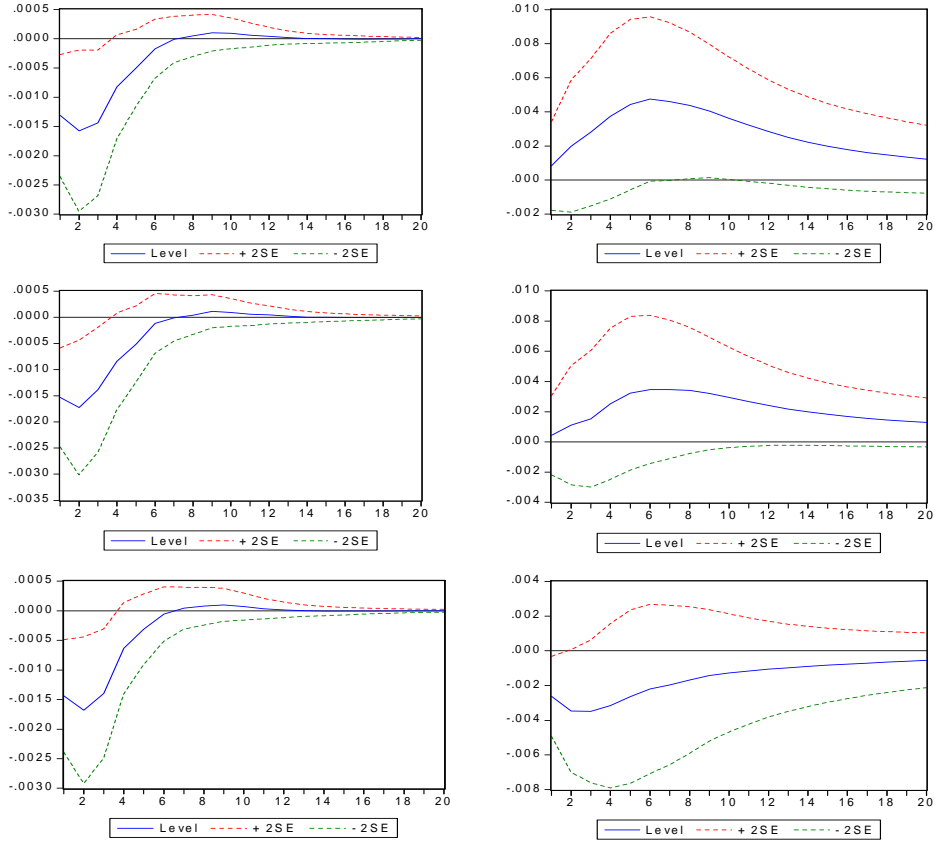


Figure 10: Response of employment to different productivity measures

Figure 10 shows that that for the case of the data in first differences, a technology shock reduces employment. Note however that for the VAR in levels, CEV’s VAR, the impulse responses move from positive territory to statistically significant negative territory. Note further, that the response to employment now becomes stronger than the response to hours and is likely to explain why total hours per capita worked fall. Hence, as for the case of Galí’s VARs, when we correct for potential changes in productivity, in CEV’s VARs, it is employment and not hours which appear to dominate the overall impact of a technology shock on total hours worked per capita. This somewhat changes the conclusions we had reached in section 5.1, namely that hours and not employment tended to dominate total hours. Now, it is total employment.

5.3.2 Sign restrictions

We impose sign restrictions on the impulse responses of the estimated VARs to perform sensitivity analysis on the identification schemes considered thus far. We use the techniques developed by Faust (1998), Canova and DeNicolo (2002) and Uhlig (2004) which impose restrictions on the impulse responses of the model.²² However, instead of showing specific impulse responses, we conduct a number of simulations to determine how easy it is to identify a technology shock and once that shock is identified whether it is more consistent with Galí's results or with CEV's. Essentially, we consider 50,000 possible identifications of a structural VAR in VMA form, each with same probability of being true as the VAR is under-identified. To identify the technology shock, in (25) and (26) we assume that shock ε_t has a positive effect on Δp on impact (ie the first period) and that this shock continues to have a positive effect after a number of periods (we considered 20, 40 and 60 periods) thus proxying as a permanent shock on productivity. We make the further assumption that the absolute value of the impulse responses for productivity following shocks to ε_t in (25) and ε_t^l and ε_t^n in (26) after 40 periods is close to zero (we considered 20, 40 and 60 period horizons), implying that only technology shocks have a permanent effect on productivity. Whenever those restrictions were satisfied we counted the replication as "satisfying the technology shock requirement". For each of the replications satisfying the technology shock requirement we imposed further restrictions on the impulse responses of the labour market variables to check whether the identified shock was consistent with the RBC paradigm. We did this experiment for the variables in levels and first differences. The results are reported in table 5.

Table 5 depicts a number of interesting results. First, it appears that it is somewhat easier to identify the technology shock using a bivariate VAR than a trivariate VAR, specially for the data in level form. Second, whether variables enter in levels or first differences makes a difference for the results: when variables are in levels it is easier for the identified technology shock to be consistent with the RBC paradigm. Variables in first differences are on the other hand more likely to reject the RBC paradigm and be consistent with Galí-type results.

Table 6 depicts a similar exercise as that one presented in Table 5, though we use the productivity measure that accounts for the productivity slowdown of 1973-1997. We only present the results for the simulations with 40 periods (simulations with a different number of periods did not change the results). What is interesting is that, for the two variable case,

²²For more on this technique see Appendix C.

	40 periods (baseline)	20 periods	60 periods
Levels data (2 Variables)			
Technology shocks	9427	10096	9233
RBC true	5768	5248	5826
Negative labour responses	3659	4848	3407
Differenced data (2 variables)			
Technology shocks	11706	11838	11630
RBC true	3319	3391	3244
Negative labour responses	8387	8447	8386
Levels data (3 Variables)			
Technology shocks	5383	6484	5155
RBC true	2095	2175	1995
Negative labour responses	633	1090	574
Differenced data (3 variables)			
Technology shocks	9217	9265	9422
RBC true	1535	1662	1601
Negative labour responses	3046	3050	3250

Table 5: Number of times identification achieved using unadjusted productivity measure

the number of times a negative response is obtained increases (this is also true for the three variable case, though it is less striking) with the new productivity measure. In fact, for the levels data, the results are more in line with Galí's than with the differenced data. These results thus verify Fernald's conclusions and those we obtained in section 5.3.1.²³

6 Can an alternative RBC model generate the results found in the paper?

Following Francis and Ramey (2005), we now investigate whether a variant of a RBC model is capable of explaining the results found in the data, namely that a positive technology shock reduces hours and employment. Francis and Ramey show, taking inspiration from Jerman (1998), Boldrin et al (2001), that a model with habit formation in consumption and

²³The reason why, for the three variable VARs, the RBC true and Negative labour responses rows do not add up to the number of technology shocks is because we are only reporting results where both labour variables are positive or negative on impact. Thus, situations where one of the two variables is positive and the other is negative are not reported. Of course, in those cases, the impulse responses are not consistent with an RBC model.

	Levels data (2 Variables)	Differenced data (2 variables)
Technology shocks	12833	16028
RBC true	1427	6186
Negative labour responses	11406	9842
	Levels data (3 Variables)	Differenced data (3 variables)
Technology shocks	13646	16523
RBC true	2397	3821
Negative labour responses	4417	4396

Table 6: Number of times identification achieved using break adjusted productivity measure

adjustment costs in capital is capable of producing a reduction in total hours.²⁴ It turns out that an extension of the unemployment model examined above that incorporates habit formation in consumption and adjustment costs in capital leads to the result that a positive technology shock decreases employment and hours. We first present the model equations and then show the impulse responses.

Consider the following problem:

$$\begin{aligned}
W(\tilde{S}_t) &= \max \left[u(\tilde{C}_t, \tilde{H}_t, L_t, N_t) \right] + \beta E_t W(\tilde{S}_{t+1}) \\
s.t. \tilde{K}_{t+1} &= \frac{Z_t}{Z_{t+1}} \left(\left\{ \left(\frac{a_1}{1-\gamma} \right) \left[\frac{\tilde{Y}_t - \tilde{C}_t}{\tilde{K}_t} \right]^{1-\gamma} + a_2 + (1-\delta) \right\} \tilde{K}_t - \kappa V_t \right) \\
\tilde{Y}_t &= \tilde{K}_t^\theta (N_t L_t)^{1-\theta} \\
N_{t+1} &= (1-\sigma) N_t + \chi_t V_t^\alpha [(1-N_t)e]^{1-\alpha} \\
\tilde{H}_{t+1} &= -\frac{b}{G_{Z,t+1}} \tilde{C}_t \\
u(\tilde{C}_t, \tilde{H}_t, L_t, N_t) &= \frac{N_t \phi_1 \left[(\tilde{C}_t + \tilde{H}_t)^\psi (1-L_t)^{1-\psi} \right]^{1-\tau} + (1-N_t) \phi_2 \left[(\tilde{C}_t + \tilde{H}_t)^\psi (1-e)^{1-\psi} \right]^{1-\tau}}{1-\tau} \\
&\text{plus evolution of } A \text{ and } \chi
\end{aligned}$$

where the noticeable differences reside in the introduction of habits in consumption, H (if $b = 0$ we would have the standard preferences without habits), the adjustment costs to

²⁴Campbell (1994) also shows this result but using non-separable preferences for consumption and leisure in an otherwise standard RBC model.

capital (note that if $\gamma = a_2 = 0$ and $a_1 = 1$, we would revert to the standard model without adjustment costs).²⁵

The impulse responses associated with the parameter values of table 1 plus $b = 0.9$, $\psi = 0.36$, $\tau = 1$, $\gamma = 4.38$ (these are values used by Jerman (1998) and Boldrin et al (2001)) yield the impulse responses shown in figure 11.

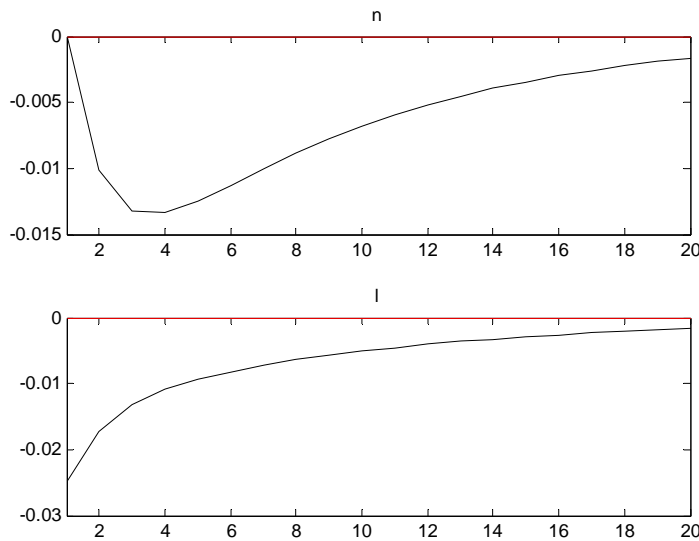


Figure 11: Responses to a technology shock

As figure 11 shows, there is a negative response of employment and labour to the technology shock consistent with the results presented previously. However, employment does not react on impact as was the case in the results presented in section 5. This suggests that a variant of this simple model is required, perhaps a model with nominal rigidities.

7 Conclusions

The aims of this paper were three-fold: first, to examine whether we could identify technology shocks in a trivariate VAR, second, whether these shocks resulted in predictions consistent with RBC models and third, to understand whether it is hours worked per person

²⁵The assumption of nonseparable preferences in consumption and labour simplify the analysis.

or employment which explain the results of the papers by Galí (1999) and CEV (2003). The reasons for moving from a bivariate VAR to a trivariate one were at least threefold: first, as Galí (2005) has pointed out, behind the trends in total hours worked lie different trends in the number of hours worked per worker and in total employment. Thus it is of importance to know whether total hours are driven by changes in total employment or in the number of hours worked per person (or both).²⁶ Our research suggests that changes in employment are the main driver of total hours worked and also that employment appears to react more than hours to technology shocks. Second, moving to a trivariate VAR enabled us to consider the sensitivity of the restrictions imposed in bivariate VARs. These alternative restrictions should allow us, in principle, to examine whether previous results in the literature were sensitive to the identifying restrictions used. Third, there are a number of statistical issues related to the measure of total hours. Given that hours worked per person in the US is $I(1)$, for total hours to be stationary total employment must be $I(1)$ and more importantly it must be cointegrated with hours per person. Imposing this restriction without testing for it (table 3 showed that it does not hold in our sample) is inefficient and is the assumption used in some bivariate VARs (most notably CEV's VAR).

The results may be summarised as follows:

1. A technology shock reduces both hours and employment if those two variables are specified in first differences, with the response of employment being stronger than the response of hours (which is not necessarily statistically significant). This result is consistent with the results found in Galí (1999) and in FR (2005).
2. A technology shock increases both hours and employment, when those two variables are specified in levels, although in this case it is employment which is not statistically significant and hours worked per person now dominate. This result is consistent with CEV (2003)'s results and is the opposite result we found in the previous point.
3. None of these results change if capital taxation or alternative measures of employment (including and excluding the government sector) are used.
4. Considering the possibility of changes in the trend growth rate of productivity does

²⁶This is an important policy issue which has recently received much attention following Prescott (2004). In that paper, Prescott suggests that lower tax rates explain why Americans work more hours than Europeans. Given the different trends in hours worked per worker and the employment ratio in the US, compared with some European countries, it would appear that the main driver in Prescott's total hours measure is total employment. This would appear to be inconsistent with Prescott's main mechanism which are distortions to the intratemporal labour supply decision. It would therefore be interesting to undertake Prescott's exercise but using Andolfatto's model and introducing taxes.

reverse the results found in point 2 but does not change the results in 1. Moreover, in this case, for the variables in levels, it is employment and not hours which tend to dominate the change in total hours worked. These results are broadly consistent with those of Fernald (2005).

5. We also performed a number of test to determine which of the identified technology shocks best represented a true technology shock. Whilst the evidence is not conclusive, the shocks identified using the VAR in first differences are probably more consistent with a technology shock.

Our overall interpretation of the results in this paper must be similar to those made by Galí (1999), FR (2005) and Fernald (2005). First, technology shocks cannot be the main drivers of the business cycle; other shocks must be accounting for the positive correlation between output, employment and hours that is observed in US data. Second, since it appears that it is employment which accounts for the movements in total hours, it would be a worthwhile exercise to consider extensions of Andolfatto (1996)'s model that are able to satisfy the results found in section 5. We have gone some way towards filling that gap by using a modified RBC model that matches certain aspects of the results shown in section 5. For instance, Galí (1999) suggests that models with nominal rigidities may do a better job of explaining the business cycle than models that rely exclusively on technology shocks. In a recent paper, Trigari (2006) incorporates nominal rigidities to a search model although she does not consider the impact of a technology shock on the labour market. Third, more work must be undertaken to understand the downward trend in the number of hours worked per capita in the US (and elsewhere - see Galí (2004)). It is possible that increased female labour force participation may explain some of the decrease in hours worked per person, so that a model with household participation may be a worthwhile endeavour.²⁷

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²⁷Further avenues of research should include the estimation of models that permit cointegration between the variables in the labour market given thereby exploiting the trends observed in hours per person and the employment ratio. Perhaps a model with output, capital and the labour market variables could be estimated employing cointegrating methods in order to identify a technology shock.

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A How data transformations affect the results of interest

We show here how the data transformations may affect how hours respond to an identified technology shock. In the first column we represent the response of total hours to a technology shock using different transformations for total hours: in levels, first differences (the source of Galí’s original results), the deviations of total hours from a linear, and quadratic trends and the deviation from a Holdrick Prescott filter. The second column performs the same transformations but in this case we use total per capita hours (the second column, first row shows the results of Christiano et al (2003)).

As figure 12 shows, the results are pretty consistent with the arguments put forward by Galí and Rabanal (2004): for most transformations of hours, the response of hours to a technology shock is negative.

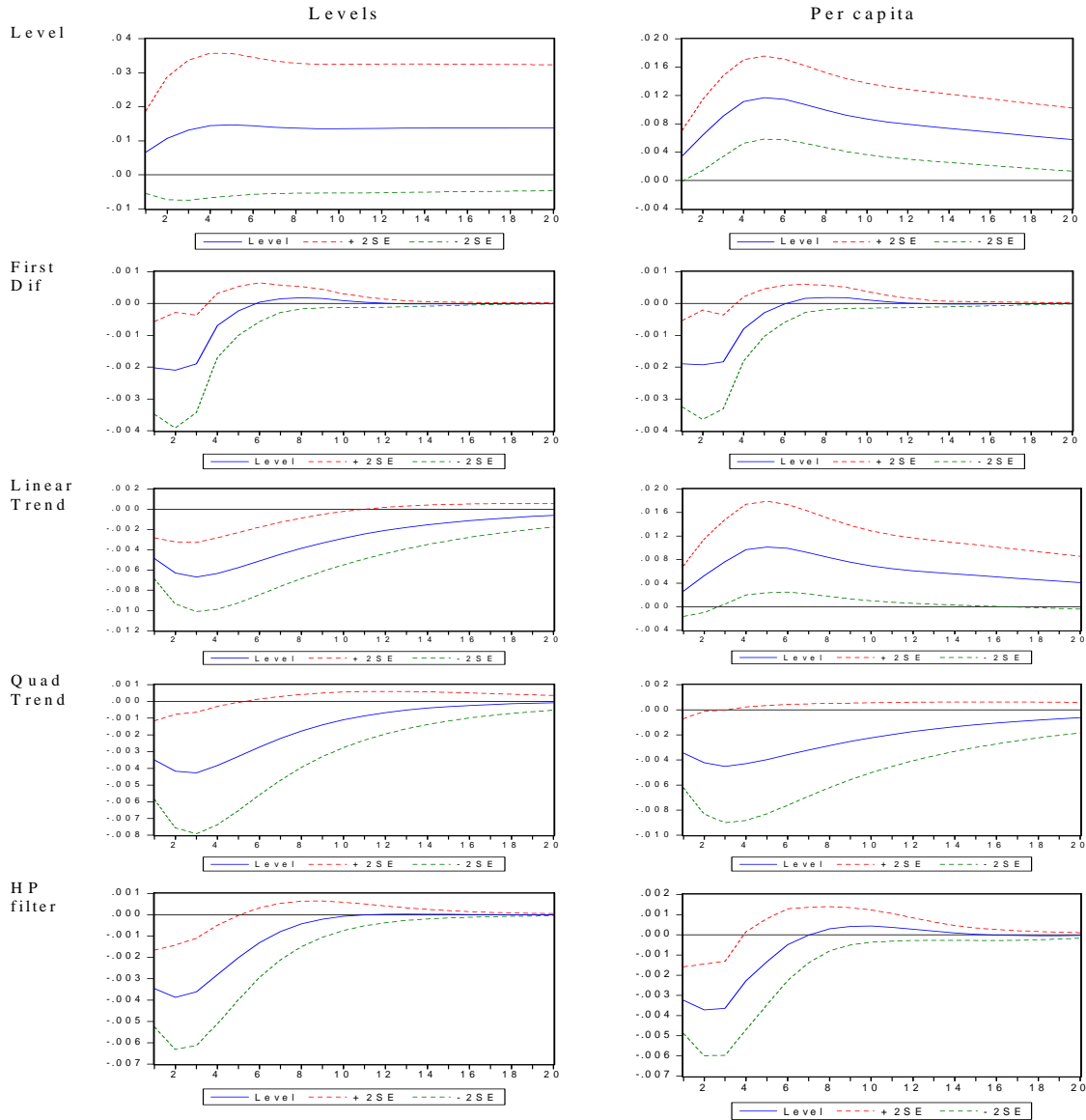


Figure 12: Different data transformations and the effect of technology shocks

B How guilty is our data?

In this Appendix we consider whether our data definitions and/or sample size could have been responsible for the results encountered in the main text. In order to test these hypothesis we

re-estimate the VARs of FR over the period 1965Q1 to 2003Q1 using their data and compare results with our own data definitions. This allows us to test two hypothesis: first, whether the exclusion of the period 1947 to 1964 is responsible for our results, and second, whether our data differs substantially from the data used by FR. This exercise is only conducted for the VARs in first differences (a la Galí) and in levels (a la CEV).

Figure 13 shows the results for VARs estimated in first differences. It presents three rows, each showing the response of productivity and total hours worked to a one percentage shock to identified technology. The first row presents the results of FR using their data, the second row whether the shorter sample 1965Q1 to 2003Q1 may have an impact on the results and the final row presents the results when our data are used over a sample period consistent with the shorter period using FR’s data. We see that there are little differences across data periods (first and second rows) and data definitions (second and third rows) suggesting that our data and sample should not be the main drivers of the results presented in the main text. Note, that as in FR we see that following a technology shock, productivity increases but total hours fall.

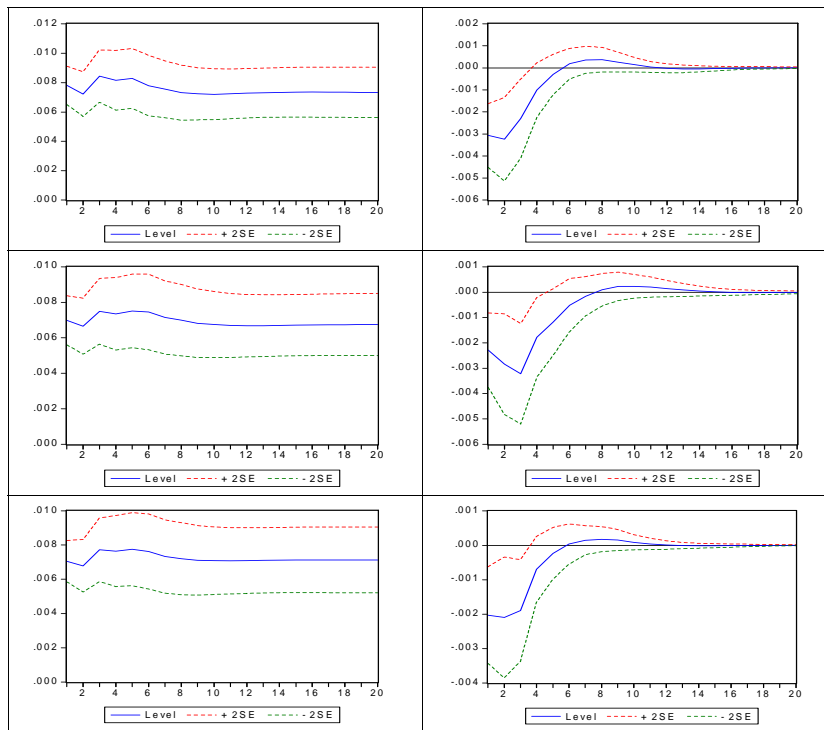


Figure 13: Impact of a shorter data sample, differences

Figure 14 shows that there are very little differences in the impulse responses regardless of the sample or data definitions used when the data is defined in as in CEV (ie levels), although the significance of the impulse responses regarding hours per capita diminishes as the sample is shortened: following a technology shock, productivity and hours both increase, though the impact of hours, using the smaller data set is statistically insignificant.

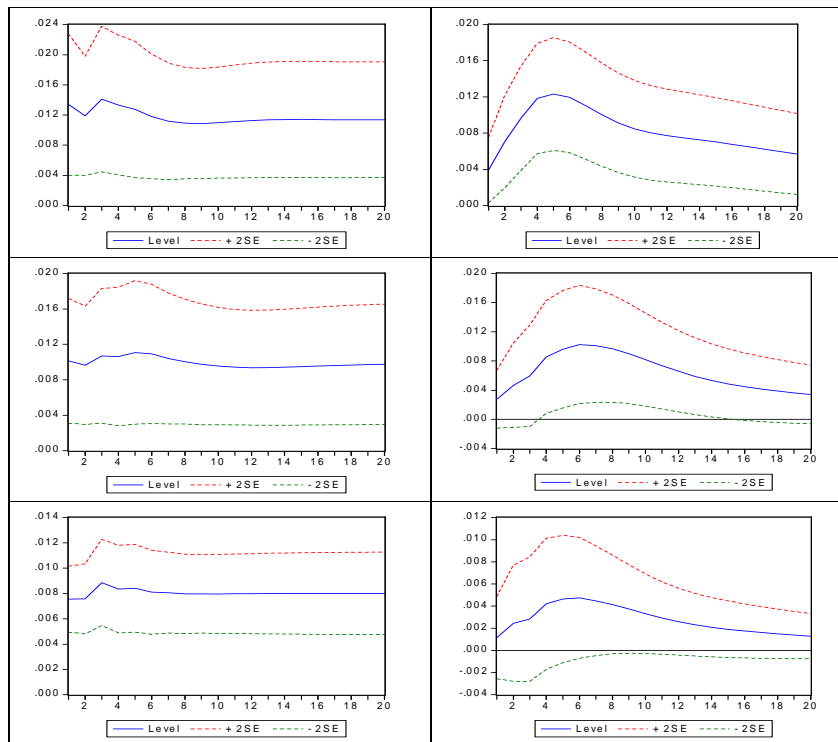


Figure 14: Impact of a shorter data sample, levels

C Sign restrictions

To illustrate the approach consider the problem of identifying the structural VAR from the reduced form VAR both in vector moving average form:

$$\begin{aligned} \mathbf{z}_t &= \mathbf{F}(L)\boldsymbol{\xi}_t, \boldsymbol{\xi}_t \sim (0, \mathbf{I}). \\ \mathbf{z}_t &= \mathbf{G}(L)\mathbf{e}_t, \mathbf{e}_t \sim (0, \boldsymbol{\Omega}_r). \end{aligned}$$

where the first VMA is the structural VAR we wish to identify and the second is the estimated reduced form VAR. Thus we wish to identify \mathbf{F} in

$$\mathbf{e}_t = \mathbf{F}\boldsymbol{\xi}_t.$$

Given the assumptions made about \mathbf{e}_t and $\boldsymbol{\xi}_t$ (the structural shocks are orthogonal and are normalised to one) the variance covariance matrix of the reduced form errors is equal to:

$$\boldsymbol{\Omega}_r = \mathbf{F}\boldsymbol{\Omega}_s\mathbf{F}' = \mathbf{F}\mathbf{F}'. \quad (27)$$

Whilst \mathbf{F} is obviously unknown, a matrix \mathbf{Q} may exist exists such that

$$\mathbf{F}\mathbf{F}' = \mathbf{F}\mathbf{Q}\mathbf{Q}'\mathbf{F}' = \mathbf{M}\mathbf{M}' = \boldsymbol{\Omega}_r \quad (28)$$

$$\mathbf{e}_t = \mathbf{F}\mathbf{Q}\mathbf{Q}'\boldsymbol{\xi}_t. \quad (29)$$

\mathbf{Q} must have certain properties for (27) and (28) to be consistent with each other:

$$\mathbf{Q}\mathbf{Q}' = \mathbf{I} \quad (30)$$

ie it must be orthonormal thus restricting the class of such matrices. Equations (28) and (29) imply that the first two moments for \mathbf{e}_t (and $\boldsymbol{\xi}_t$) are unchanged; yet (29) suggests that for every matrix \mathbf{Q} , the impact that the structural shock (and the structural shock itself) has on the variables of our structural VAR changes. To see this note that \mathbf{Q} transforms the variables as follows:

$$\mathbf{e}_t = \underbrace{\mathbf{F}\mathbf{Q}\mathbf{Q}'}_{\mathbf{F}^*} \boldsymbol{\xi}_t^*$$

and therefore we have defined a new structural shock, $\boldsymbol{\xi}_t^* = \mathbf{Q}'\boldsymbol{\xi}_t$, and a new structural matrix $\mathbf{F}^* = \mathbf{F}\mathbf{Q}$. Neither \mathbf{e}_t nor the variance covariance matrix of the reduced form residuals has

changed. Thus, by considering different matrices for \mathbf{Q} satisfying (30) then we can consider alternative shocks and alternative impulse responses. Obviously the set of matrices \mathbf{Q} that can be considered must be restricted to some finite number in order to make this approach operational.

Canova and De Nicolò (2002) make use of the following decomposition of the matrix $\mathbf{\Omega}_r$:

$$\mathbf{\Omega}_r = \mathbf{P}\mathbf{G}\mathbf{P}' \quad (31)$$

where \mathbf{P} is a matrix of eigenvectors and \mathbf{G} a diagonal matrix of eigenvalues (on the main diagonal). Then equating (28) and (31) implies that

$$\begin{aligned} \mathbf{F}\mathbf{F}' &= \mathbf{P}\mathbf{G}\mathbf{P}' \\ \implies \mathbf{F} &= \mathbf{P}\mathbf{G}^{0.5}. \end{aligned}$$

Then

$$\mathbf{P} = \prod_{m,n} \mathbf{Q}_{m,n}(\theta)$$

where the \mathbf{Q} s are Givens rotation matrices where $0 < \theta \leq \pi/2$ and the subscript (m, n) indicates that rows m and n are rotated by the angle θ . Selecting orthonormal matrices \mathbf{Q} our decomposition becomes

$$\mathbf{P}\mathbf{G}^{0.5}\mathbf{Q}_{m,n}(\theta)\mathbf{Q}_{m,n}(\theta)'\mathbf{G}^{0.5}\mathbf{P}' = \mathbf{\Omega}_r.$$

Thus, starting from an eigenvalue, eigenvector decomposition it is possible to decouple such decomposition in one direction or another for each θ . What one needs to determine is the range over which to consider the θ s and what Givens rotations to use. The number of Givens rotations to consider is a function of the number of variables in the VAR. If the VAR is $N \times N$ where $N = 3$ then there will be a total of 4 possible rotation matrices:

$$\begin{aligned} &\begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}, \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ 0 & 1 & 0 \\ \sin \theta & \cos \theta & 1 \end{bmatrix}, \\ &\begin{bmatrix} 1 & \cos \theta & -\sin \theta \\ 0 & \sin \theta & \cos \theta \\ 0 & 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & \cos \theta & -\sin \theta \\ 0 & 1 & 0 \\ 0 & \sin \theta & \cos \theta \end{bmatrix} \end{aligned}$$

if $N = 4$ there will be 9, and so on. The next step is to define the grid of values for θ . Canova and De Nicolò grid the interval $[0, \pi/2]$ into M points and construct in the four

variable ($N = 4$) system $9M$ orthogonal decompositions of Ω_r . An alternative form of selecting the matrices is to draw the θ s from a uniform distribution and perform a given number of simulations.²⁸

²⁸Other \mathbf{Q} matrices include the householder:

$$\mathbf{H} = \mathbf{I} - 2\mathbf{x}\mathbf{x}' / (\mathbf{x}'\mathbf{x})$$

where \mathbf{x} is a vector of uniform random variables on -1 to 1 interval. Another consideration is a modification of the Givens rotation:

$$\mathbf{Q} = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 & \cdots & 0 & \vdots \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \cos \theta & -\sin \theta & \cdots & 0 & 0 \\ 0 & 0 & \cdots & -\sin \theta & -\cos \theta & \cdots & 0 & 0 \\ \vdots & 0 & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \vdots & 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 1 \end{bmatrix}.$$

We used these alternative rotations and the results did not change much.