Technology Shocks and Aggregate Fluctuations: How Well Does the RBC Model Fit Postwar U.S. Data?*

Jordi Galí † Pau Rabanal ‡

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Abstract

Answer: not so well. We reach that conclusion after reviewing recent research efforts that seek to identify and estimate the role of technology as a source of economic fluctuations, in a way more direct than the early RBC literature. The bulk of the evidence suggests a very limited role for aggregate technology shocks, pointing instead to demand factors as the main force behind the strong positive comovement between output and labor input measures that is the hallmark of the business cycle.

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‡International Monetary Fund

1. Introduction

Since the seminal work of Kydland and Prescott (1982) and Prescott (1986) proponents of the Real Business Cycle (RBC) paradigm have claimed a central role for exogenous variations in technology as a source of economic fluctuations in the postwar U.S. economy. Those fluctuations have been interpreted by RBC economists as the economy's response to exogenous variations in technology, in an environment with perfect competition and intertemporally optimizing agents, and in which the role of nominal frictions and monetary policy is, at most, secondary.

Behind the claims of RBC theory lies what must have been one the most earth-shattering findings in postwar macroeconomics: a calibrated version of the neoclassical growth model augmented with a consumption-leisure choice and with stochastic changes in total factor productivity as the only driving force can gnerate is sufficient to account for the bulk of economic fluctuations in industrialized countries. In practice, accounting for observed fluctuations has meant that calibrated RBC models match pretty well the patterns of unconditional second moments of a number of macroeconomic time series, including their relative standard deviations and correlations. Such findings led Prescott to claim "...that technology shocks account for more than half the fluctuations in the postwar period, with a best point estimate near 75 percent,"[1] Similarly, in their assessment of the road traveled and the lessons learned by RBC theory after more than a decade, Cooley and Prescott (1989) could confidently claim that "it makes sense to think of fluctuations as caused by shocks to productivity."

While most macroeconomists have recognized the methodological impact of the RBC research program and have adopted its modelling tools, other important, more substantial ele-

[1] Prescott (1996b)

ments of that program have been under a growing challenge in recent years. First, the widely acknowledged importance of monetary policy in industrialized economies, has led the bulk of the profession to move away from both real models or frictionless monetary models when trying to understand short run macroeconomic phenomena. Secondly, and most importantly for the purposes of this paper, the view of technological change as a central force behind cyclical fluctuations has been called into question. In the present paper we aim at providing an overview of the literature that has challenged the central role of technology in business cycles.

A defining feature of the literature reviewed below lies in its effort to look for evidence on the role of technology that is "more direct" than just checking whether any given model driven by technology shocks, and more or less plausibly calibrated, can generate the key features of the business cycle. In particular we discuss efforts 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.

Much of that literature (and, hence, much of the present paper) focuses on one central, uncontroversial feature of the business cycle in industralized economies, namely, the strong positive comovement between output and labor input measures. That comovement is illustrated graphically in Figure 1, which displays the quarterly time series for hours and output in the U.S. nonfarm business sector over the period 1948:1-2002:4. In both cases the original series have been transformed using the band-pass filter developed in Baxter and King (1994), calibrated to remove fluctuations of periodicity outside an interval between 6 and 32 quarters. As in Stock and Watson (1999) we interpret the resulting series as reflecting fluctuations associated with business cycles.

As is well known, the basic RBC model can generate fluctuations in labor input and output of magnitude, persistence, and degree of comovement *roughly* similar to the series displayed in Figure 1. Furthermore, when the actual sequence of technology shocks (proxied by the estimated disturbances of an AR process for the Solow residual) is fed as an input into the model, the resulting equilibrium paths of output and labor input track surprisingly well the observed historical patterns of those variables, as shown in King and Rebelo (1999) in what amounts to a more stringent test than the usual moment-matching exercises.

The literature reviewed in the present paper asks, however, very different questions: what are the effects of technology shocks in actual economies? How do they differ from the predictions of standard RBC models? What is their contribution to business cycle fluctuations? What features must be incorporated in business cycle models to account for the observed effects? The remainder of this paper describes some of the tentative and often contradictory answers that the efforts of a growing number of researchers have yielded. It is not easy to summarize in a few words the wealth of existing evidence nor to agree on some definite conclusions of a literature that is still very much ongoing. Nevertheless, it is safe to state that the bulk of the evidence reviewed in the present paper provides very little support to the initial claims of the RBC literature on the central role of technological change as a source of business cycles.

The remainder of the paper is organized as follows. Section 2 reviews some of the early papers that questioned the importance of technology shocks, and presents some of the basic evidence regarding the effects of those shocks. Section 3 discusses a number of criticisms and possible pitfalls of that literature. Section 4 presents the case for the existence of nominal frictions as an explanation of the estimated effects of technology shocks. Section 5 summarizes some of the real explanations for the same effects found in the literature. Section 6 lays out and analyzes an estimated DSGE model that incorporates both nominal and real frictions, and evaluates their respective role. Section 7 concludes.

2. Estimating the Effects of Technology Shocks

In Galí (1999) the effects of technology shocks were estimated by means of a structural VAR approach. In its simplest specification, to which we restrict our analysis here, the empirical model makes use of information on two variables: output and labor input, which we denote respectively by y_t and n_t, both expressed in logs. Those variables are used to construct a series for (log) labor productivity, $x_t \equiv y_t - n_t$ which, in what follows, is assumed to be integrated of order one (in a way consistent with the evidence reported below). The joint behavior of labor productivity growth (Δx_t) and some stationary transformation of labor input ($\widehat{n}_t$) is then assumed to have the following MA representation

$$\begin{bmatrix} \Delta x_t \\ \widehat{n}_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^d \end{bmatrix} \equiv C(L)\ \varepsilon_t \tag{2.1}$$

where ε_t^z and ε_t^d are serially uncorrelated, mutually orthogonal structural disturbances, whose variance is normalized to unity. Estimates of the distributed lag polynomials $C^{ij}(L)$ are obtained by a suitable transformation of the estimated reduced form VAR for $[\Delta x_t, \widehat{n}_t]$ after imposing the long run identifying restriction $C^{12}(1) = 0$.[2] That restriction "defines" $\{\varepsilon_t^z\}$ and $\{\varepsilon_t^d\}$ as shocks *with* and *without* a *permanent* effect on labor productivity, respectively. On the basis of some of the steady state restrictions shared by a broad range of macro models (and further discussed below) Galí (1999) proposes to interpret permanent shocks to productivity $\{\varepsilon_t^z\}$ as *technology*

[2] See Blanchard and Quah (1989) and Galí (1999) for details.

shocks. On the other hand, transitory shocks $\{\varepsilon_t^d\}$ would potentially capture a variety of driving forces behind output and labor input fluctuations that would not be expected to have permanent effects on labor productivity. The latter include shocks that could potentially have a permanent effect on output (but not on labor productivity), but which are "non-technological" in nature, as would be the case for some permanent shocks to preferences or goverment purchases, among others.[3] As discussed below, they could in principle capture *transitory* technology shocks as well.

2.1. Revisiting the Basic Evidence on the Effects of Technology Shocks

Next, we revisit and update the basic evidence on the effects of technology shocks reported in Galí (1999). Our baseline empirical analysis uses quarterly U.S. data for the period 1948:I-2002:IV. Our source is the Haver USECON database, for which we list the associated mnemonics. Our series for output corresponds to nonfarm business sector output (LXNFO). Our baseline labor input series is hours of all persons in the nonfarm business sector (LXNFH). Unless otherwise noted, the estimates below are based on a per capita tranformation of the output and hours series, using a measure of civilian noninstitutional population aged 16 and over (LNN).

Our baseline estimates are based on a specification of hours in first-differences, i.e. we set $\widehat{n}_t = \Delta n_t$. That choice seems consistent with the outcome of ADF tests applied to the hours series, which do not reject the null of a unit root in the level of hours at a 10 percent significance level, against the alternative of stationarity around a linear deterministic trend. On the other hand, the unit root null for the first-differenced series at level of less than 1 percent.[4] Consistently

[3] It is precisely that feature what differentiates the approach to identification in G99 from that in Blanchard and Quah (1989). The latter used restrictions on long-run effects on output, as opposed to labor productivity.

[4] With four lags, the t statistics are -2.5 and and -7.08 the level and first-difference, respectively.

with the previous result, a KPSS test applied to n_t rejects the stationarity null at a less than 1 percent level, while failing to reject the same null when applied to Δn_t. In addition, the same battery of ADF and KPSS tests applied to our x_t and Δx_t series support the existence of a unit root in labor productivity, a necessary condition for the Galí (1999) identification scheme to make sense. Both observations suggest the specification and estimation of a VAR for $[\Delta x_t, \Delta n_t]$. Henceforth, we refer to the latter as the *difference* specification.

Figure 2 displays the estimated effects of a positive technology shock, of size normalized to one standard deviation. The graphs on the left show the dynamic responses of labor productivity, output, and hours, together with ($\pm$) two standard error bands.[5] The corresponding graphs on the right show the simulated distribution of each variable's response *on impact.* As in Galí (1999), the estimates point to a significant and persistent decline in hours after a positive technology shock that raises labor productivity permanently. The point estimates suggest that hours do eventually return to (close to) to their original level, but not until more than a year later. That pattern of hours generates, as a result, a positive but muted initial response of output in the face of a positive technology shock. Notice that the distribution of the impact effect on hours assigns a zero probability to an increase in that variable.

The estimated impulse responses to a technology shock shown in the previous figure contrast starkly with the implications of a standard calibrated RBC model, which would predict a positive comovement among the three variables plotted in the figure in response to that shock.[6]

Not surprisingly, the previous estimates have dramatic implications regarding the sources of the business cycle fluctuations in output and hours displayed in Figure 1. This is illustrated

[5] That distribution is obtained by means of a Montecarlo simulation based on 500 drawings from the distribution of the reduced-form VAR distribution.

[6] See, e.g., King et al. (1988) and Campbell (1994)

in Figure 3, which displays the estimated business cycle components of the historical series for output and hours associated with technology and non-technology shocks. In all cases the initial estimated components have been detrended using the same band-pass filter underlying the series plotted in Figure 1. As in Galí (1999), the picture that emerges is very clear: fluctuations in hours and output driven by technology shocks account for a small fraction of the variance of those variables at business cycle frequencies: 5 and 7 percent, respectively. Furthermore, the comovement at business cycle frequencies between output and hours resulting from technology shocks is shown to be essentially zero (the correlation is -0.08), in contrast with the high positive comovement observed in the data (0.88). Clearly, the pattern of technology-driven fluctuations, as identified in our structural VAR, shows little resemblance with the conventional business cycle fluctuations displayed in Figure 1.

The picture changes dramatically we turn our attention to the estimated fluctuations of output and hours driven by shocks with no permanent effects on productivity (and which are referred to as non-technology shocks in the graph). Those shocks account for 95 and 93 of the variance of the business cycle component of hours and output, respectively. In addition, they generate a nearly perfect correlation (0.96) between the same variables. In contrast with its technology-driven counterpart, this component of output and hours fluctuations displays a far more recognizable business cycle pattern.

2.2. Related Empirical Work

The empirical connection between technological change and business cycle fluctuations has been the focus of a rapidly expanding literature. Here we mention some of the key papers using U.S. data, leaving for later those whose findings relate more specifically to the content of other sections.

An early contribution to that literature is given by the relatively unknown paper by Blanchard, Solow and Wilson (1995). That paper already spells out some of the key arguments found in the subsequent literature. In particular, it stresses the need to isolate the component of productivity which is the result of exogenous technological improvements. They adopt a simple instrumental variables approach, with a number of demand-side variables assumed to be orthogonal to exogenous technological change used as instruments for employment growth or the change in unemployment in a regression that features productivity growth as a dependent variable. The fitted residual in that regression is interpreted as a proxy for the technology-driven changes in productivity. When they regress the change in unemployment on the "filtered" productivity growth variable they obtain a positive coefficient, i.e. an (exogenous) increase in productivity drives the unemployment rate up. A dynamic specification of that regression suggests that such an effect lasts for about three quarters, after which unemployment starts to fall and returns rapidly to its original value.

As mentioned Galí (1999, footnote 19) the finding of a decline in hours (or an increase in unemployment) in reponse to a positive technology shock can also be detected in a number or earlier VAR papers, though that finding often goes unnoticed or is presented as puzzling. Blanchard and Quah (1989) and Blanchard (1989) are exceptions in that they provide some explicit discussion of the finding, which they interpret as consistent with a traditional Keynesian model "in which increases in productivity...may well increase unemployment in the short run if aggregate demand does not increase enough to maintain employment".[7]

The work of Basu, Fernald and Kimball (1999; BFK, henceforth) deserves a special attention

[7] Blanchard (1989, p. 1158).

here, given its focus and the similarity of its findings to those in Galí (1999) despite the use of an unrelated methodology. BFK used a sophisticated growth accounting methodology allowing for increasing returns, imperfect competition, variable factor utilization and sectoral compositional effects. in order to uncover a time series index of aggregate technological change in the postwar US economy. Their approach, combining elements of earlier work by Hall (1990) and Basu and Kimball (1997) among others, can be viewed as an attempt to cleanse the Solow residual (Solow (1957)) of widely acknowledeged measurement error resulting from the strong assumptions underlying its derivation. Estimates of the response of the economy to innovations in their measure of technological change point to a sharp short run decline in the use of inputs (including labor) when technology improves, with ouput showing no significant change (and possibly even a small decline). After that short-run impact both variables gradually adjust upward, with labor input returning to its original level and with output reaching a permenently higher plateau after a lag of several years.

Kiley (1996) extends the structural VAR framework in Galí (1999) to U.S. two-digit manufacturing industries. He finds that technology shocks induce a negative correlation between employment and output growth in 12 of the 17 industries considered. When he estimates an analogous conditional correlation for employment and productivity growth, he obtains a negative value for 15 out of 17 industries. Francis (2001) conducts a similar analysis, though he is able to better identify for industry-specific technology shocks by including a measure of aggregate technology, which is assumed to be exogenous to each of the industries considered. He finds that, for the vast majority of industries, labor input measure decline in response to a positive technology shock.

Shea (1998) uses a structural VAR approach to model the connection between variations over time measures of technological innovation (R&D and number of patent applications) and subsequent changes in TFP and hired inputs, using industry level data. For most specifications and industries he finds that an innovation in the technology indicator does not cause any significant change in TFP, and tends to increase labor inputs in the short run. While not much stressed by Shea, however, one of the findings in his paper is particularly relevant for our purposes: in the few VAR specifications for which a significant increase in TFP is detected in response to an innovation in the technology indicator, inputs–including labor–are shown to respond in the direction opposite to the movement in TFP, a finding to which we will return below.[8]

Francis and Ramey (2003a) extend the analysis in Galí (1999) in several dimensions in order to check the robustness of the main findings. Among other modifications they consider, they augment the baseline VAR (specified in first differences) with a capital tax rate measure in order to sort out the effects of technology shocks from those of permanent changes in tax rates (more below). Secondly, they identify a technology shocks as those with permanent effects on real wages (as opposed to labor productivity) and/or no long run effects on hours, both equally robust predictions of a broad class of models that satisfy a balance growth property. Those alternative identifying restrictions are not rejected when combined into a unified (overidentified) model. Francis and Rameyshow that both the model augmented with capital tax rates and the model with alternative identifying restrictions (considered separately or jointly) imply impulse responses to a technology shock similar to those in Galí (1999) and, in particular, a drop in hours in response to a positive technology shock. Francis, Owyang and Theodorou (2003) use a variant of the sign restriction algorithm of Uhlig (1999) and show that the finding of a negative response of hours to a positive technology shock is robust to replacing the restriction on the

[8] See the comment on Shea's paper by Galí (1998) for a more detailed discussion of that point.

asymptotic effect of that shock with one taking imposing a positive response of productivity at a horizon of ten years after the shock.

A number of papers have provided related evidence based on non-U.S. aggregate data. In Galí (1999) the framework discussed in the previous section was also applied to the remaining G7 countries (Canada, the U.K., France, Germany, Italy, and Japan). He uncovers a negative reponse of employment to a positive technology shock in all countries, with the exception of Japan. Galí (1999) also point out some differences in those estimates relative to those obtained for the U.S.: in particular, the (negative) employment response to in Germany , the U.K. and Italy appears to be larger and more persistent, which could be interpreted as evidence of "hysteresis" in European labor markets. Very similar qualitative results for the euro area as a whole can also be found in Galí (2004), which applies the same empirical framework to the quarterly data set which has become recently available. In particular, technology shocks are found to account for only 5 percent and 9 percent of the variance of the business cycle component of euro area employment and output, respectively, with the corresponding correlation between their technology-driven components being -0.67). Francis and Ramey (2003b) estimate a structural VAR with long-run identifying restrictions using long-term U.K. annual time series tracing back to the nineteenth century; they find robust effidence of a negative short-run impact of technology shocks on labor in every subsample.[9] Finally, Carlsson (2000) develops a variant of the empirical frameworks in BFK (1999) and Burnside et al. (1995) to construct a time series for technological change, and appplies it to a sample of Swedish two-digit manufacturing industries. Most prominetly, he find that positive shocks to technology have, on impact, a contractionary

[9] The latter evidence contrasts with their analysis of long term U.S. data, in which the results vary significantly across samples and appear to depend on the specification used (more below).

effect on hours and a non-expansionary effect on output, as in BFK (1999).

2.3. Implications

The implications of the evidence presented above for business cycle analysis and modelling are manifold. Most significantly, those findings reject a key prediction of the standard RBC paradigm, namely, the positive comovement of output, labor input and productivity in response to technology shocks. That positive comovement is the single main feature of that model that accounts for its ability to generate fluctuations that resemble business cycles. Hence, taken at face value, the evidence presented above rejects in an unambiguous fashion the empirical relevance of the standard RBC model. It does so in two dimensions. First, it shows that a key features of the responses to aggregate technology shocks predicted by calibrated RCB models are not observed in the data. Second, and perhaps more importantly, since one such feature–namely the positive comovement between ouput and labor input measure–is a defining characteristic of the business cycle it follows as a corollary that technology shocks cannot be the quantitatively important (and, even less, a dominant) source of aggregate fluctuations in industrialized economies. The latter implication is particularly damning for RBC theory, given its traditional emphasis on aggregate technology variations as a source of business cycles, but its relevance is independent of one's views on the true model.

3. Possible Pitfalls in the Estimation of the Effects of Technology Shocks

This section has two main objectives. First, we try address a question that is often raised regarding the empirical approach used in Galí (1999): to what extent can we be confident in the economic interpretation given to the identified shocks and, in particular, in the mapping between technology shocks and the nonstationary component of labor productivity? Below we provide some evidence that makes us feel quite comfortable about that interpretation. Second, we describe and address some of the econometric issues that Christiano, Eichenbaum, and Vigfusson (2003) have raised in a recent paper, and which focus mostly on the suitability of the specification of hours (levels or first differences). Finally, we discuss a recent paper by Fisher (2003) which distinguishes between two types of technology shocks, neutral and investment-specific.

3.1. Are Long Run Restrictions Useful in Identifiying Technology Shocks?

The approach to identification proposed in Galí (1999) relied on the assumption that only (permanent) technology shocks can have a permanent effect on (average) labor productivity. That assumption was argued to hold under relatively weak conditions that would be satisfied by a broad range of models, including RBC and New Keynesian ones. To review the basic argument consider an economy whose technology can be described by an aggregate production function[10]

$$Y_t = F(K_t, A_t N_t) \tag{3.1}$$

where Y denotes output, K is the capital stock, N is labor input and A is an index of technology. Under the assumption that F is homogeneous of degree 1, we have

$$\frac{Y_t}{N_t} = A_t \; F_k\,(k_t, 1) \tag{3.2}$$

[10] An analogous but somewhat more detailed analysis can be found in Francis and Ramey (2003a)

where $k_t \equiv \frac{K_t}{A_t N_t}$ is the ratio of capital to labor (expressed in efficiency units). For a large class of models characterized by an underlying balanced growth path, the marginal product of capital F_k must satisfy, along that path, a condition of the form

$$(1-\tau)\ F_k\,(k,1) = (1+\mu)\ \left(\rho+\delta+\frac{\gamma}{\sigma}\right) \tag{3.3}$$

where μ is the price markup, τ is a tax on capital income, ρ is the time discount rate, δ is the depreciation rate, σ is the intertemporal elasticity of substitution, and γ is the average growth rate of (per capita) consumption and output. Under the assumption of decreasing returns to capital, it follows from (3.3) that the capital labor ratio k will be stationary (and will thus fluctuate around a constant mean) so long as all the previous parameters are constant (or stationary). In that case, (3.2) implies that only shocks that have a permanent effect on the technology parameter A can be a source of the unit root in labor productivity, thus providing the theoretical underpinning for the identification scheme in Galí (1999).

How plausible are the assumptions underlying that identification scheme? Preference or technology parameters like ρ, δ, σ, and γ are generally assumed to be constant in most examples and applications found in the business cycle literature. The price markup μ is more likely to vary over time, typically as a result of some embedded price rigidities; in the latter case, however, it is likely to remain stationary, fluctuating around its desired or optimal level. In the event that desired markups (or the preference and technology parameters listed above) displayed some non stationarity, the latter would arguably be more likely to take the form of some smooth function of time, which should be reflected in the deterministic component of labor productivity, but not in its fluctuations at cyclical frequencies.[11] Finally, it is important to notice that the previous approach to identification of technology shocks requires that (i) F_k be decreasing, so that k is uniquely pinned down by (3.3), and (ii) that the technology process $\{A_t\}$ is exogenous (at least with respect to the business cycle). The previous assumptions have been commonly adopted by business cycle modelers.[12]

3.1.1. The Unit Root in Labor Productivity: Do Capital Income Tax Shocks Play a Role?

The previous argument, however, is much less appealing when applied to the capital income tax rate. As Uhlig (2004) and others have pointed out, the assumption of either a constant or stationary capital income tax rate may be unwarranted, given the observed behavior of measures for that variable over the postwar period. This is illustrated graphically in Figure 4, which displays two alternative measures of the capital income tax rate in the U.S.. Figure 4.A displays a quarterly series for the average capital income tax rate constructed by Jones (2002) for the period 1958:I-1997:IV. Figure 4.B shows an annual measure of the average marginal capital income tax rate constructed by Ellen McGrattan for the period 1958-1992 and which corresponds to an updated version of the one used in McGrattan (1994).[13] Henceforth we denote those series by τ_t^J and τ_t^M, respectively. Both series display an apparent non-stationary behavior, with highly persistent fluctuations. This is confirmed by a battery of ADF tests, which fail to reject the null hypothesis of a unit root in both series, at conventional significance levels.

[11] Of course that was also the traditional view regarding technological change, but one that was challenged by the RBC school.

[12] Exceptions include stochastic versions of endogenous growth models, as in King et al. (1988b). In those models any transitory shock can , in principle, have a permanent effect on the level of capital or disembodied technology and, as a result, on labor productivity.

[13] We are grateful to Craig Burnside and Ellen McGrattan for providing the data.

Furthermore, as evidenced in Figures 4.C and 4.D, which display the same series in first differences, the presence of sizeable short-run variations in those measures of capital taxes could hardly be captured by means of some deterministic or smooth function of time (their standard deviations being 0.79 % for the quarterly Jones series and 2.4 % for the annual McGrattan series). In fact, in both cases that first-differenced series $\Delta\tau_t$ shows no significant autocorrelation, suggesting that a random walk process can approximate the pattern of capital income tax rates pretty well.

The previous evidence, combined with the theoretical analysis above, points to a potential caveat in the identification approach followed in Galí (1999): the shocks with permanent effects on productivity estimated therein could be capturing the effects of permanent changes in tax rates (as opposed to those of genuine technology shocks). That "mislabeling" could potentially account for the empirical findings reported above.

Francis and Ramey (2003a) attempt to overcome that potential shortcoming of the identification strategy by augmenting the VAR with a capital tax rate variable, in addition to labor productivity and hours. As mentioned earlier, the introduction of the tax variable is shown not to have any significant influence on the findings: positive technology shocks still lead to short run declines in labor [though it is not clear how technology and tax rate shocks are distinguished in that paper].

Here we revisit the hypothesis of the "tax rate shock mistaken for a technology shock" by looking for evidence of some comovement between (i) the "permanent" shock series estimated above using long run restrictions, and (ii) each of the two capital tax series, in first-differences. Given the absence of significant autocorrelation in $\Delta\tau_t^J$ and $\Delta\tau_t^M$, we interpret each of those those series as (alternative) proxies for the shocks to the capital income tax. Also, when using the McGrattan series, we annualize the "permanent" shock series obtained from the quarterly VAR by averaging the shocks corresponding to each natural year.

The resulting evidence can be summarized as follows. First, innovations to the capital income tax rate show a near zero correlation with the permanent shocks from the VAR. More precisely, our estimates for $corr(\Delta\tau_t^J, \varepsilon_t^T)$ and $corr(\Delta\tau_t^M, \varepsilon_t^T)$ are, respectively, -0.06 and 0.12, neither of which is significant at conventional levels. Thus, it is highly unlikely that the permanent VAR shocks may be capturing exogenous shocks to capital taxes.

Secondly, an OLS regression of the Jones tax series $\Delta\tau_t^J$ on current and lagged values of ε_t^T yields jointly insignificant coefficient estimates: the significance level is 0.54.when four lags are included, 0.21 when we include eight lags. A similar result obtains when we regress the McGrattan tax series $\Delta\tau_t^M$ on current and several lags of ε_t^T, with the significance level for the null of zero coefficients being 0.68 when four lags are included (0.34 when we use 8 lags). Since the sequence of those coefficients corresponds to the estimated impulse response of capital taxes to the permanent VAR shock, the previous evidence suggests that the estimated effects of the permanent VAR shocks are unlikely to be capturing the impact of any possible induced (i.e. endogenous) response in capital taxes to whatever exogenous shock underlies the estimated permanent VAR shock.

We conclude from the previous exercises that there is no support for the hypothesis that the permanent shocks to labor productivity, interpreted in Galí (1999) as technology shocks, could be instead capturing changes in capital income taxes.[14]

[14] A similar conclusion is obtained by Fisher (2003), using a related approach in the context of the multiple technology shock model described below.

3.1.2. Permanent Shocks to Labor Productivity: Are they Really Capturing Variations in Technology?

Having all but ruled out variations in capital taxes as a significant factor behind the unit root in labor productivity, we next present some evidence that favors the interpretation of the VAR permanent shock as a shock to technology. In addition we also provide some evidence against the hypothesis that transitory variations in technology may be a significant force behind the shocks identified as transitory shocks, a hypothesis that cannot be ruled out on purely theoretical grounds.

Francis and Ramey (2003a) test a weak form of the hypothesis of permanent shocks as technology shocks, by looking for evidence of Granger-causality from a number of indicators that are viewed as independent of technology and the identified technology shock. The indicators include the Romer and Romer (1989) monetary shock dummy, the Hoover and Perez (1994) oil shock dummies, Ramey and Shapiro's military buildup dates (1998), and the federal funds rate. None of them have a significant predictive power for the estimated technology shock.

Here we provide a more direct assessment by making use of the measure of aggregate technological change obtained by Basu, Fernald and Kimball (1999; BFK, henceforth).[15] As discussed earlier, those authors constructed that series using an approach unrelated to ours. The BFK variable measures the annual rate of technological change in the U.S. nonfarm private business sector. The series has an annual frequency and covers the period 1950-1989. Our objective here is to assess the plausibility of the technology-related interpretation of the VAR shocks obtained above by examining their correlation with the BFK measure. Given the differences in frequencies

[15] In particular, we use their "fully corrected" series.

we annualize both the "permanent" and "transitory" shock series obtained from the quarterly VAR by averaging the shocks corresponding to each natural year.

The main results can be summarized as follows. First, the correlation between the VAR-based permanent shock and the BFK measure of technological change is positive and significant at the 5 percent level, with a point estimate of 0.45. The existence of a positive contemporaneous comovement is apparent in Figure 5, which displays the estimated VAR permanent shock together with the BFK measure (both series have been normalized to have zero mean and unit variance, for ease of comparison).

Secondly, the correlation between our estimated VAR transitory shock and the BFK series is slightly negative, but insignificantly different from zero in any case (the point estimate is -0.04). The bottom graph of Figure 5, which displays both series, illustrates the absence of any obvious comovement between the two.

Finally, and given that the BFK series is mildly serially correlated, we have also run a simple OLS regression of the (normalized) BFK variable on its own lag, and the contemporaneous estimates of the permanent and transitory shocks from the VAR. The estimated equation, with t statistics in brackets, is given by:

$$BFK_t = \underset{(1.85)}{0.29}\, BFK_{t-1} + \underset{(2.16)}{0.67}\, \varepsilon_t^z - \underset{(-1.11)}{0.32}\, \varepsilon_t^d$$

which reinforces the findings obtained from the simple contemporaneous correlations.

In summary, the results from the above empirical analysis suggest that the VAR-based permanent shocks may indeed be capturing exogenous variations in technology, in a way consistent with the interpretation made in Galí (1999). In addition, we cannot find evidence supporting the view that the VAR transitory shocks–which were shown in Section 2 to be the main source of business cycle fluctuations in hours and output–may be related to changes in technology.

Before we conclude this section we mention a recent paper by Erceg, Guerrieri and Gust (2003) that analyzes the reliability of the identification of technology shocks based on the long run restrictions used in Galí (1999). They so so by means of Monte Carlo simulations based on two alternative calibrated DSGE models: a standard RBC model and a new Keynesian model with staggered wage and price setting. Both models satisfy the long run restriction that makes technology the only source of the unit root productivity. They conclude that the estimated responses to a technology shock using the Galí (1999) VAR approach look like the true responses to that shock in both models, at least from a qualitative viewpoint. However they also point to some non-negligible bias in the estimates which can be largely traced to the fact to the slow adjustment of the capital stock in response to a permanent change in technology, and the existence of shocks that may have highly persistent, though ultimately transitory, effects on productivity and which may get confounded with technology shocks.

3.2. Robustness to Alternative VAR Specifications

In a recent paper, Christiano, Eichenbaum, and Vigfusson (2003; CEV, henceforth) have questioned some of the VAR-based findings in Galí (1999) regarding the effects of technology shocks, on the basis of their lack of robustness to the transformation of labor input used. In particular, CEV argue that first-differencing the (log) of per capita hours may distort the sign of the estimated response of that variable to a technology shock, if that variable is truly stationary. Specifically, their findings based on a bivariate VAR model in which (per capita) hours are specified in levels ($\widehat{n}_t = n_t$) imply that output, hours, and productivity all rise in response to a positive technology shock. On the other hand, when they use a difference specification they obtain results similar to the ones reported above, involving a negative comovement between output (or productivity) and hours in response to technology shocks. Perhaps most interestingly, CEV discuss the extent to which the findings obtained under the level specification can be accounted for under the assumption that the difference specification is the correct one, and viceversa. Given identical priors over the two specifications, that "encompassing" analysis leads them to conclude that the odds in favor of the level specification relative to the difference specification are about 2 to 1. CEV obtain similar results when incorporating additional variables in the VAR.

Our own estimates of the dynamic responses to a technology shock when we specify (per capita) hours in levels do indeed point to some qualitative differences. In particular, as shown in Figure A1 in the appendix, the point estimate of the impact response of hours worked to a positive technology is now positive, though very small. Yet, and in contrast with the findings in CEV, that impact effect and indeed the entire dynamic response of hours is not significantly different from zero. The sign of the point estimates, however, is sufficient to generate a positive correlation (0.88) between output and hours conditional on the technology shock (see Figure B1). Furthermore, as illustrated in Figure B1 and reported in the second row of Table 1, under the level specification, technology shocks still account for a (relatively) small fraction of the variance of output and hours at business cycle frequencies (37 and 11 percent, respectively), though that fraction is larger than the one implied by the difference specification estimates.[16]

While we find the encompassing approach adopted by CEV enlightening, their strategy of

[16]With the exception of their bivariate model under a level specification, CEV also find the contribution of technology shocks to the variance of output and hours at business cycles to be small (below 20 percent). In their bivariate, level specification model that contribution is as high as 66 and 33 percent, respectively.

pairwise comparisons with uniform priors (which mechanically assigns a $\frac{1}{2}$ prior to the level specification) may lead to some bias in the conclusions. In particular, a simple look at a plot of the time series for (log) per capita hours worked in the U.S.over the postwar period, displayed in Figure 6, is not much suggestive of stationarity, at least in the absence of any further transformation. In particular, and in agreement with the ADF and KPSS tests reported above, the series seems perfectly consistent with a unit root process, though possibly not a pure random walk. On the basis of a cursory look at the same plot, and assuming that one wishes to maintain the assumption of a stationary process for the stochastic component of (log) per capita hours, a quadratic function of time would appear to be a more plausible characterization of the trend than just the constant implicit in CEV's analysis. In fact, an OLS regression of that variable on a constant, time and time squared yields a highly significant coefficient associated with both time variables. Furthermore, a test of a unit root on the residual from that regression fails to reject that hypothesis, while the KPSS does not reject the null of stationarity, at a 5 percent significance level in both cases.[17] Figure 6 displays the fitted quadratic trend and the residual variables, illustrating graphically that point. When we re-estimate the dynamic responses to a technology shock using detrended (log) per capita hours we find again a decline in hours in response to positive technology shock (see Figure A2), and a slighly negative (-0.11) conditional correlation between the business cycle components of output and hours. In addition, the estimated contribution of technology shocks to the variance of output and hours is very small (7 and 5 percent, essentially the same as under difference specification; see Table 1).

In order to further assess the robustness of the above results we have also conducted the same

[17] Given the previous observations one wonders how an identical prior for both specifications could be assumed, as CEV do when computing the odds ratio.

analysis using a specification of the VAR using an alternative measure of labor input, namely, (log) *total* hours, without a normalization by working age population. As it should be clear from the discussion in section 3.1, the identification strategy proposed in Galí (1999) and implemented here should be valid independently of the measure of labor input used, since labor productivity in invariant to that normalization.[18] The bottom three rows in Table 1 as well as Figures A3-A5 and B3-B5 report the results corresponding to three alternative transformations of that variable analyzed (first differences, levels, detrended). In the three cases a positive technology shock is estimated to have a strong and statistically significant negative impact on hours worked, at least in the short run. Interestingly, under the level and detrended transformations that negative response of hours is sufficiently strong to pull down output in the short-run, despite the increase in productivity. Note however that the estimated decline in output is not significant in either case.[19] Furthermore, the estimated contribution of technology shocks to the variance of the business cycle component of output and hours is small in all cases, with the largest share being 36 percent of the variance of hours, obtained under the level and detrended specifications.

As a final check on the robustness of our findings, we have re-estimated all the model specifications discussed above using employment as labor input measure (instead of hours), and real GDP as an output measure. A summary of our results for the six specifications considered using employment and GDP can be found in Table 2. The results under this specification are much more uniform: independently of the transformation of employment used, our estimates point to a decline in employment in the short run, as well as a very limited contribution of technology shocks to the variance of GDP and employment. We should stress that those findings

[18] In fact, total hours was the series used originally in Galí (1999).

[19] The finding of a slight short run decline in output was obtained in BFK (1999).

obtain even when we specify employment rate in levels, even though the short run decline in employment is not statistically significant in that case.

In summary, the previous robustness exercise based on postwar U.S. data has shown that for all but one of the transformations of hours used the basic finding in Galí (1999), namely, that of a decline in labor input in response to a positive technology shock. The exception corresponds to the level specification of per capita hours, but even in that case the estimated positive response of hours does not appear to be significant. In most cases the contribution of technology shocks to the variance of the cyclical component of output and hours is very small, and always below 40 percent. Finally, and possibly with the exception mentioned above, the pattern of comovement of output and hours at business cycle frequencies resulting from technology shocks, fails to resemble the one associated with postwar U.S. business cycles.

Additional evidence on the implications of alternative transformations of hours using annual time series spanning more than a century is provided by Francis and Ramey (2003b). Their findings based on US data point to considerable sensitivity of the estimates across subsample periods and the choice of transformation for hours. They assess the validity of the diffferent specifications they look at their implications for the persistence of the productivity response to a non-technology shock, the plausibility of the patterns of estimated technology shocks, as well as the predictability of the latter (the Hall-Evans test). On the basis of that analysis they conclude that first-differenced and, to a lesser extent, quadratically detrended hours yields are the most plausible specification. Francis and Ramey show that in their data those two preferred specifications generate a short run negative comovement beteen hours and output in response to a shock that has a permanent effect on technology in the postwar period. In the pre-WWII period, however, the difference specification yields an increase in hours in response to a shock that raises productivity permanently. On the other hand, when they repeat the exercise using UK data (and a difference specification) they find a clear negative comovement of employment and output both in the pre-WWII and postwar sample periods.

In light of those results and the findings in the literature discussed above, we conclude there is no clear evidence favoring a conventional RBC interpretation of economic fluctuations as being largely driven by technology shocks, at least when the latter take the form assumed in the standard one-sector RBC model. Next we consider how the previous assesment is affected once we allow for technology shocks that are sector specific.

3.3. Investment-Specific Technology Shocks

In a series of papers, Greenwood, Hercowitz, and Huffman (1998), and Greenwood, Hercowitz, and Krusell (1997, 2000; henceforth, GHK) put forward and analyzed a version of an RBC model in which the main source of technological change is specific to the investment sector. In the proposed framework, and in contrast with the standard RBC model, a technology shock does not have any immediate impact on the production function. Instead, it affects the rate of transformation between current consumption and productive capital in the future. Thus, any effects on current output must be the result of the ability of that effect in eliciting a change in the quantity of input services hired by firms. GHK (1997, 2000) motivate the interest in studying the potential role of investment-specific technology shocks by pointing to the large variations in measures of the relative price of new equipment constructed by Gordon (1990), both over the long-run as well as at business cycle frequencies. In particular, GHK (2000) analyze a calibrated model in which investment-specific technology shocks and conclude that the latter can account for about 30 percent of US output fluctuations, a relatively modest figure compared to the claim of the earlier RBC literature regarding the contribution of aggregate, sector-neutral technology shocks in calibrated versions of one-sector RBC models.

In a recent paper, Fisher (2003) revisits the evidence on the effects of technology shocks and their role in the US business cycle, using an empirical framework that allows for separately identified sector-neutral and investment-specific technology shocks (which, following Fisher, we refer to as respectively as N-shocks and I-shocks, for short). In a way consistent with Galí (1999) both types of technology shocks are allowed to have a permanent effect on labor productivity (in contrast with non-technology shocks). Yet, and in a way consistent with the GHK framework, only investment-specific technology shocks are allowed to affect permanently the relative price of capital goods. Using times series for labor productivity, per capita hours, and the price of equipment (as a ratio to the consumption goods deflator) and an approach equivalent to the structural VAR methodology mentioned above, Fisher estimates impulse responses to the two types of shocks, and their relative contribution to business cycle fluctuations. We have conducted a similar exercise on our own, and summarized some the findings in Table 3.[20] For each type of technology shock and specification the table reports its contribution to the variance of the business cycle component of output and hours, as well as the implied conditional correlation between those two variables.

The top panel in Table 3 corresponds to three specifications using per capita hours worked, the labor input variable to which Fisher (2003) restricts his analysis. Not surprisingly our results essentially replicate some of his findings. In particular, we see that under the three transformations of considered, N-shocks are estimated to have a negligible contribution to the variance of output and hours at business cycle frequencies, and to generate a very low correlation

[20] We thank Jonas Fisher for kindly providing the data on real investment price.

between those two variables.

The results for I-shocks are different in at least two respects. Firstly, and as stressed in Fisher (2003), I-shocks generate a high positive correlation between output and hours. The last column of Table 3 tells us that such a result holds for all labor input measures and transformations considered. As argued in the introduction, that property must be satisfied by any shock that plays a central role as a source of business cycles. Of course, this is a necessary, not a sufficient condition. Whether the contribution of I-shocks to business cycle fluctuations is large or not depends once again on the transformation of labor input used. Table 3 shows that when that variable is specified in levels, it accounts for more than half of the variance of output and hours at business cycle frequencies, a result that appears to be independent of the specific labor input measure used. On the other hand, when hours or employment are specified in first diferences or are quadratically detrended the contribution becomes much smaller, and always remains below one-fourth.

What do we conclude from the previous exercise? First of all, the evidence does not speak with a single voice: whether a technology shocks are given a prominent role or not as source of business cycles depends on the transformation of the labor input measure used in the analysis. Perhaps more interestingly, the analysis of the previous empirical model makes it clear that if some form of technological change plays a significant role as a source of economic fluctuations, it is not likely to be of the aggregate, sector-neutral kind that the early RBC literature emphasized, but of the investment-specific kind stressed in GHK (2000). Finally, and leaving aside the controversial question of the importance of technology shocks, the previous findings, as well as those in Fisher (2003), raise a most interesting issue: why do I-shocks appear to generate the sort of strong positive comovement between output and labour input measures that characterizes business cycles, while that property is conspicuously absent when we consider N-shocks? Below we attempt to provide a partial explanation for this seeming paradox.

4. Technology Shocks, Nominal Rigidities and The Role of Monetary Policy

One possible interpretation of the "anomalous" response of employment to technology shocks, put forward both in Galí (1999) and BFK (1999), relies on the presence of nominal rigidities. As a matter of principle, nominal rigidities should not, *in themselves*, necessarily be a source of the observed employment response. Nevertheless, and as emphasized in GLV, when prices are not fully flexible, the equilibrium response of employment (or, for that matter, of any other endogenous variable) to any real shock (including a technology shock) is *not* invariant to the monetary policy rule in place; in particular, it will be shaped by how the monetary authority reacts to the shock under consideration. Different monetary policy rules will thus imply different equilibrium responses of output and employment to a technology shock, ceteris paribus.

Galí (1999) provided some intuition behind that result by focusing on the simple case of an economy with an interest-inelastic money demand (so that the relationship $y_t = m_t - p_t$ holds in equilibrium), price-setting in advance (implying predetermined price level), and a simple money-supply based monetary policy. In that context, it is clear that unless the central bank endogenously expands the money supply (at least) in proportion to the increase in productivity, employment will experience a short-run decline. Galí (2003) shows that the previous finding generalizes (for a broad range of parameter values) to an economy with staggered-price setting, and a more realistic interest elasticity of money demand, but still an exogenous money supply.

In that case, even though all firms will experience a decline in their marginal cost only a fraction of them will adjust their prices downwards in the short run. Accordingly, the aggregate price level will decline, and real balances and aggregate demand will rise. Yet, when the fraction of firms adjusting prices is sufficiently small, the implied increase in aggregate demand will be less than proportional to the increase in productivity. That, in turn, induces a decline in aggregate employment.

Many economists have criticized the previous argument on the grounds that it relied on a specific and unrealistic assumption regarding how monetary policy is conducted, namely, that of a money-based rule (Dotsey (2002), McGrattan (1999)). In the next subsection we address that criticism by analyzing the effects of technology shocks in the context of a simple illustrative model with a more plausible staggered price-setting structure, and a monetary policy characterized by an interest rate rule similar to the one proposed by Taylor (1993). The model is simple enough to generate closed-form expressions for the responses of output and employment to variations in technology, thus allowing us to illustrate the main factors shaping that response and thus generating a negative comovement between the two variables.

4.1. A Simple Illustrative Model

The model we use to illustrate the role of nominal rigidities and monetary policy in shaping the effects of technology shocks is a standard New Keynesian framework with staggered price setting a la Calvo (1983). Its equilibrium dynamics can be summarized as follows. On the demand side output is determined by a forward-looking IS-type equation:

$$y_t = E_t\{y_{t+1}\} - \sigma \ (r_t - E_t\{\pi_{t+1}\}) \tag{4.1}$$

where y_t denotes (log) output, r_t is the nominal interest rate, and $\pi_t \equiv p_t - p_{t-1}$ denotes the rate of inflation between $t-1$ and t. Parameter σ can be broadly interpreted a measure of the sensitivity of aggregate demand to changes in interest rates and, thus, of the "effectiveness" of monetary policy.

Inflation evolves according to a forward-looking new Keynesian Phillips curve

$$\pi_t = \beta \, E_t\{\pi_{t+1}\} + \kappa \, (y_t - \overline{y}_t) \tag{4.2}$$

where $\overline{y}_t$ is the natural level of output (or potential output, for short), defined as the one that would prevail in the absence of nominal frictions. Equivalently, $\overline{y}_t$ can be interpreted as the equilibrium output generated by some background real business cycle model driven by technology. The previous equation can be derived from the aggregation of optimal price-setting decisions by firms subject to price adjustment constraints à la Calvo. In that context, coefficient κ is inversely related to the degree of price stickiness: stronger nominal rigidities imply a smaller response of inflation to any *given* sequence of output gaps.[21]

For simplicity we assume that exogenous random variations in productivity are the only source of fluctuations in the economy and, hence, the determinants of potential output. Accordingly, we postulate the following reduced form expression for potential output:[22]

$$\overline{y}_t = \overline{\psi}_y \, a_t \tag{4.3}$$

[21] See Galí, Gertler, and López-Salido (xxxx) or Sbordone (xxxx) for a derivation that allows for decreasing returns to labor.

[22] Such a reduced form relationship would naturally arise as an equilibrium condition of a simple RBC model with productivity as the only state variable.

where a_t represents an exogenous technology parameter. The latter is assumed to follows an AR(1) process $a_t = \rho_a \; a_{t-1} + \varepsilon_t$, where $\rho_a \in [0,1]$. Notice that under the assumption of an aggregate production function of the form $y_t = a_t + (1-\alpha) \; n_t$, we can derive the following expression for the natural level of employment $\overline{n}_t$

$$\overline{n}_t = \overline{\psi}_n \; a_t$$

where $\overline{\psi}_n \equiv \frac{\overline{\psi}_y - 1}{1-\alpha}$. Since we want to think of the previous conditions as a reduced-form representation of the equilibrium of a standard calibrated RBC model (without having to specify its details), it is natural to assume $\overline{\psi}_y \geq 1$ (and, hence, $\overline{\psi}_n > 0$). In that case, a positive technology shock generates an increase in both output and employment, as generally implied by the RBC models under conventional calibrations. Notice that it is precisely that property which makes it possible for any technology-driven RBC model to generate equilibrium fluctuations which replicate some key features of observed business cycles, including a positive comovement of output and employment.[23]

Finally, and given (4.1) and (4.3), we can determine the natural real interest rate as being given by

$$\begin{aligned} \overline{rr}_t &= \sigma^{-1} E_t\{\Delta \overline{y}_{t+1}\} \\ &= -\sigma^{-1}(1-\rho_a)\overline{\psi}_y \; a_t \equiv \overline{\psi}_{rr} \; a_t \end{aligned}$$

[23] The absence of another state variable (say, capital stock or other disturbances) implies a perfect correlation between the natural levels of output and employment, in contrast with existing RBC models in the literature where that correlation is positive and very high, but not one.

The latter expression gives the only pattern for the real interest rate which can support potential output, and which is uniquely pinned down by the RBC model. Thus, in the absence of nominal frictions, prices will adjust in response to shocks so that, given the specification of monetary policy, the real interest rate matches its natural counterpart at all times (since this is the only real rate that guarantees a level of demand that exactly matches the level output, which is determined by supply factors).

In the presence of the sort of nominal rigidities assumed here, however, there is no reason why the equality between the real interest rate and its natural counterpart should hold, for equilibrium output (and in general other endogenous real variables) is not determined independently of the response of nominal interest rates and inflation. Under our assumptions, the central bank could implement the frictionless equilibrium by following a rule that implies that the nominal rate behaves in equilibrium according to $r_t = \overline{rr}_t$ while the price level is fully stabilized.

But, as illustrated below, to the extent that the monetary policy rule adopted in practice implies a different behavior for the nominal interest rate, the response of output and employment to technology shocks (as well as other real shocks) will differ from that implied by the RBC model.

In that context, a natural question that arises is the extent to which the comovement of output and employment in response to technology shocks found in the evidence described above may have been the result of the way monetary policy has been conducted in the U.S. and other industrialized economies. In order to illustrate that point, we embed in the context of the simple model above, by deriving the implications for the effects of technology shocks of having the central bank follow an interest rate rule of the form

$$r_t = \phi_\pi \, \pi_t + \phi_y \, y_t \tag{4.4}$$

A rule similar to (4.4) has been proposed by Taylor (1993) and others as a good characterization of monetary policy in the U.S. and other industrialized economies in recent decades. Notice that, as in Taylor, we assume that the monetary authority responds to output (or its deviations from trend), and not to the output gap. We view this as a more realistic description of actual policies (which emphasize output stabilization), and consistent with the fact that the concept of potential output used here, while necessary to construct any measure of the output gap, cannot be observed by the policymaker.[24]

Combining (4.4) with equilibrium conditions (4.1) and (4.2), we can derive the following closed-form expression for equilibrium output:

$$\begin{aligned} y_t &= \Theta \, \overline{\psi}_y \, a_t \\ &\equiv \psi_y \, a_t \end{aligned}$$

where

$$\Theta \equiv \frac{\kappa(\phi_\pi - \rho_a)}{(1-\beta\rho_a)[\sigma^{-1}(1-\rho_a) + \phi_y] + \kappa(\phi_\pi - \rho_a)}$$

Notice that under the (weak) assumption that $\phi_\pi > \rho_a$, we have $0 < \Theta \leq 1$. The fact that $\Theta > 0$ guarantees that a positive (negative) technology shock raises (lowers) output, as in the

[24] Throughout we assume that the condition $\kappa(\phi_\pi - 1) + (1-\beta)\phi_y > 0$ is satisfied. As shown by Bullar and Mitra () that condition is necessary to guarantee a unique equilibrium.

standard RBC model. On the other hand, $\Theta \leq 1$ implies that

$$\psi_y \leq \overline{\psi}_y$$

i.e., in the presence of nominal frictions the size of response of output to a technology shock, ψ_y, is bounded above by that implied by the corresponding RBC model ($\overline{\psi}_y$) when the central bank follows rule (4.4). Hence, the combination of sticky prices and a Taylor rule will tend to over-stabilize the output fluctuation resulting from technology shocks. We can interpret parameter Θ as an index of *effective policy accommodation*, i.e. one that measures the extent to which Taylor rule (4.4) accommodates the changes in potential output resulting from variations in technology shocks, given the persistence of the latter and the rest of parameters describing the economy. Notice that the index of effective policy accommodation Θ is increasing in the size of the inflation coefficient in the Taylor rule (ϕ_π), and in the effectivenes of interest changes (as reflected by σ). It is also positively related to κ (and, hence, inversely related to the degree of price stickiness). On the other hand, it is inversely related to the size of the output coefficient in the Taylor rule (ϕ_y). Notice that full accommodation (and, hence, replication of the efficient response), can only be attained in the limiting cases of (i) price flexibility ($\kappa \to \infty$), (ii) extreme policy response to deviations of inflation from target ($\phi_\pi \to \infty$), and (c) random-walk technology ($\rho_a = 1$) combined with strict inflation targeting ($\phi_y = 0$).[25]

[25] In order to obtain some intuition for the degree of policy accommodation in response to the technology shock, it is useful to analyze the equilibrium response of the (ex-ante) real rate $rr_t \equiv r_t - E_t\{\pi_{t+1}\}$, which is given by:

$$rr_t = -\Theta \ \ \overline{\psi}_y \ \sigma(1-\rho_a) \ a_t = \Theta \ \overline{\psi}_{rr} \ a_t \equiv \psi_{rr} \ a_t$$

Notice that while ψ_{rr} and $\overline{\psi}_{rr}$ are both negative, we have $|\psi_{rr}| \leq \left|\overline{\psi}_{rr}\right|$. Thus, in the model considered here, a central bank following a simple Taylor rule will tend to adjust real interest rates in the right direction, but less than it would be necessary to replicate the frictionless equilibrium generated by the RBC model. As a result, in response to a positive technology shock, aggregate demand will increase by less than it would be required in

Let us now turn to the equilibrium response of employment to a technology shock, which is given by:

$$\begin{aligned} n_t &= \left(\frac{\Theta \overline{\psi}_y - 1}{1 - \alpha} \right) a_t \\ &\equiv \psi_n \, a_t \end{aligned}$$

Notice that, in a way analogous to the output case, we have $\psi_n \leq \overline{\psi}_n$. In other words, the size of the employment response to a (positive) technology shock in the presence of nominal frictions is bounded above by the size of the response generated by the underlying frictionless RBC model. Furthermore, it is clear that the impact of a technology shock on employment may be positive or negative, depending on the configuration of parameter values. In particular, employment will decrease in response to a positive technology shock if the following condition is satisfied:

$$\Theta \, \overline{\psi}_y < 1 \tag{4.5}$$

i.e., if the elasticity of potential output with respect to technology *or/and* the degree of policy accommodation of changes in potential ouput are sufficiently low. In that case technology shocks would generate a negative comovement between output and employment, in a way consistent (at least qualitatively) with the empirical evidence described in section 2. What features of the economy will tend to facilitate the emergence of that outcome? From the analysis above we

order to absorb the full increase in potential output. Conversely, in the face of a negative technology shock, the real rate rises too little relative to the frictionless case, keeping output above potential and triggering an increase in inflation in spite of the decline in output. For completeness, the reponse of inflation is given by

$$\pi_t = \frac{\kappa}{1 - \beta \rho_a} \, (y_t - \overline{y}_t) = - \, \frac{\overline{\psi}_y \, \kappa (1 - \Theta)}{1 - \beta \rho_a} \, a_t \equiv \psi_\pi \, a_t$$

know that a low accommodation requires the presence of some of the following features:

- strong nominal rigidities (low κ)
- a weak monetary policy response to inflation (ϕ_π above but close to unity).
- strong concern for output stability (high ϕ_y)
- low sensitivity of aggregate demand to interest rate changes (low σ)

On the other hand, a low elasticity of potential ouput with respect to technology variations (low $\overline{\psi}_y$) will be influenced by a variety of features associated with the underlying RBC model. Those have been studied in detail in the literature and include, among others but prominently, the persistence of the shock, the elasticity of intertemporal substitution, and the (Frisch) labor supply elasticity. Using a standard calibrated RBC model, Campbell (1994) obtains a range of values for $\overline{\psi}_y$ between 1 and 2.7, depending on the persistence of the shock and the elasticity of labor supply; in particular, given a unit labor supply elasticity and a 0.95 autocorrelation in the technology process, he obtains an elasticity $\overline{\psi}_y$ of 1.45 , which we adopt as our benchmark value. [26]

What is a reasonable value for the degree of accommodation Θ? We can get a sense by looking at conventional values used in calibration exercises involving similar models and based on features of the U.S. economy. Thus, Rotemberg and Woodford's (1999) estimates based on the response to monetary policy shocks, imply a value of 0.024 for κ. A unit value is often used as an upper bound for σ. Taylor's widely used values for ϕ_π and ϕ_y are 1.5 and 0.5, respectively.

[26] Impact elasticity (Ignores subsequent adjustment of capital, which is very small). Obtained from Table 3 in Campbell (1994), with an appropriate adjustment to correct for his (labor-augmenting) specification of techology in the production function (need to divide by 2/3).

In standard RBC calibrations the assumption $\rho_a = 0.95$ is often made. Finally we can set $\beta = 0.99$ and $\alpha = \frac{1}{3}$, two values that are not much controversial. Under those assumptions, we obtain a value for Θ of 0.28. The latter figure points to a relatively low degree of effective policy accommodation. In combination with our benchmark value for $\overline{\psi}_y$ it clearly satisfies condition (4.5), with an elasticity of employment ψ_n of -0.87 .

The previous calibration exercise, while admittedly quick and loose, illustrates that far from being a condition with no possible practical relevance, (4.5) is likely to hold under a broad range of reasonable calibrations. Under those circumstances, and subject to the caveat implied by the simplicity of the model and the characterization of monetary policy, it is hard to interpret the negative comovement between output and employment observed in the data as a puzzle, as it has often been done.

In his seminal paper, Prescott (1986) concluded his description of the predictions of the RBC paradigm by stating: "In other words [RBC] theory predicts what is observed. Indeed, if the economy did not display the business cycle phenomena, there would be a puzzle." In light of the analysis above, perhaps we should think of turning Prescott's dictum over its head, and argue instead that if as a result of technology variations the economy did indeed display the typical positive comovement between output and employment that characterizes the business cycle, then there would be a puzzle!

4.1.1. Nominal Rigidities and the Effects of Investment-Specific Technology Shocks

Interestingly, the logic behind the impact of nominal rigidities on the effects of conventional aggregate, sector neutral technology shocks on which the previous discussion focuses, would also seem consistent with the estimated effects of investment-specific technology shocks, as reported in Fisher (2003) and in section.x.x above. The argument can be made most clearly in the context of a sticky price version of a model like that in GHK (2000) model. Once again, let us for simplicity that the relationship $y_t = m_t - p_t$ holds in equilibrium, and that both m_t and p_t are pre-determined relative to the shock. In that case firms will want to produce the same quantity of the good but, in contrast with the case of neutral technology shocks, in order to do so they will need to employ the same level of inputs since the efficiency of the latter has not been affected (only newly purchased capital goods will enhance that productivity in the future). That property of I-shocks is illustrated in in Smets and Wouters (2003a) in the context of a much richer DSGE model . In particular, those authors show that even in the presence of the substantial price and wage rigidities estimated for the U.S. economy a positive I-shock causes output and labor input to increase simultaneously, in a way consistent with the Fisher (2003) VAR evidence. In fact, as shown in Smets and Wouters (2003a) the qualitative pattern of the joint response of output and hours to an I-shock is not affected much when they simulate the model with all nominal rigidities turned off.

4.2. Evidence on the Role of Nominal Rigidities

A number of recent papers have provided evidence, often indirect, on the possible role of nominal rigidities as a source of the gap between the estimated responses of output and labor input measures to a technology shock and the corresponding predictions of an RBC model. We briefly describe a sample of those papers next.

Models with nominal rigidities imply that the response of the economy to a technology shock (or to any other shock, for that matter) will generally depend on the endogenous response of the monetary authority, and should thus not be invariant to the monetary policy regime in place. Galí, López-Salido, and Vallés (2003; henceforth, GLV) exploit that implication, and try to uncover any differences in the estimated response to an identified technology shock across subsample periods. Building on the literature that points to significant differences in the conduct of monetary olicy between the pre-Volcker and the Volcker-Greenspan periods, they estimate a four-variable structural VAR with a long run restriction as in Galí (1999) for each of those subsample periods. Their evidence points to significant differences in the estimated reponses to a technology shock. In particular, they show that the decline in hours in response to a positive technology shock in much more pronounced in the pre-Volcker period, being hardly significant in the Volcker-Greenspan. That evidence is consistent with the idea that monetary policy in the latter period has focused more on the stabilization of inflation, an not so much on the stabilization of economic activity. In terms of the simple model developed above, that would be associated with a higher index of effective monetary policy accommodation Θ, and hence a smaller decline in labor in the face of a technology shock.

The analysis in GLV (2003) is extended by Francis, Owyang, and Theodorou (2004) to other G7 countries. They uncover substantial differences across countries in the joint response of employment, prices and interest rates to technology shocks, and argue that some of those differences can be grounded in differences in the underlying interest rate rules.

Marchetti and Nucci (2004) use a detailed data set containing information on output, inputs and price-setting practices for a large panel of Italian manufacturing firms. Using a modified Solow residual approach they contruct a time series for total factor productivity at the firm level, and estimate the responses of a number of firm variables to an innovation in the corresponding technology measure. Among other findings, they provivide evidence of a negative impact effect of a technology shock on labor input. Most interestingly, however, Marchetti and Nucci also exploit firm-specific information regarding the frequency of price adjustments. They split the sample of firms according to the frequency of their price revisions: “flexible” price firms (adjust prices every three months or more often) and “sticky” price firms (adjusting every six months or less often). They find that the negative response of employment to a positive technology shock is larger (and significant) in the case of “sticky” price firms, and much weaker (and statistically insignificant) for “flexible” price firms. That evidence suggests that nominal rigidities may be one of the factors underlying the estimated effects of technology shocks.

[A more negative assessment on the role of nominal rigitities is found in Chang and Hong (2003). four-digit U.S. manufacturing industries. Weak evidence of contractionary effects and correlation with measures of price stickiness]

5. Real Explanations for the Negative Comovement between Hours and Output in Response to Technology Shocks

Several authors have proposed explanations for the evidence described in Section 2 that do not rely on the presence of nominal rigidities. Such “real” explanations generally involve some modification of the standard RBC model. Next we briefly describe some of those explanations.

Francis and Ramey (2003a) propose two modifications of an otherwise standard RBC model that can potentially account for the negative comovement of output and hours in response to a technology shock. The first model incorporates habit formation in consumption and capital adjustment costs. As shown in Francis and Ramey a calibrated version of that model can account for many of the estimated effects of technology shocks. In particular, the response to a permanent improvement in technology of consumption, investment and output is more sluggish than in the standard model with no habits or capital adjustment costs. If that dampening effect is sufficiently strong, the increase in output may be smaller than the increase in productivity itself, thus causing a reduction in hours. The latter decline is consistent with the optimal decision of households to consume more leisure (despite the higher wage) as a consequence of a dominant income effect.[27] A similar mechanism underlies the modification of the basic RBC model proposed by Wen (2001), who assumes a utility function with a subsistence level of consumption (equivalent to a constant habit).

The second modification of the RBC model proposed by Francis and Ramey (2003a) hinges on the assumption of no substitutability between labor and capital in production. In that context the only way to increase output in the short run is by increasing the workweek of capital. Furthermore, hours beyond the standard workweek generate additional disutility. In such a model a permanent increase in labor-augmenting technology is shown to generate a short run decline in hours. The intuition is simple, and in the final analysis not much different from other modifications proposed. While output increases inthe short run (due to increased investment opportunities), that increase is not sufficient to compensate for the fact that any quantity of output can now be produced with less employment (per shift) and a shorter workweek.

Rotemberg (2004) develops a version of the RBC model in which technological change diffuses much more slowly than implied by conventional specifications found in the RBC literature. The rate at which technology is adopted is calibrated on the basis of the micro studies on speed of diffusion. Rotemberg shows that when the smooth technology process is embedded in the RBC model it generates small short run fluctuations in output and employment, which are largely

[27] See Lettau and Uhlig (2000) for a detailed analysis of the properties of an RBC model with habit formation. As pointed out by Francis and Ramey, Lettau and Uhlig seem to dismiss the assumption of habits on the grounds that it yields "counterfactual cyclical behavior."

unrelated to the cyclical variations associated with detrended measured of employment and output. In particular, a positive innovation to technology that diffuses very slowly generates a very large wealth effect (relative to the size of the innovation) which in turn leads households the increase their consumption of leisure. As a result, both hours and output experience a short run decline in response to a technology shock of a typical size, before they gradually increase above their initial levels. Because those reponses are so smooth, they imply very small movements at cyclical frequencies. It follows that technology shocks with suchcharacteristics will only account for a small fraction of observed cyclical fluctuations in output and hours.

Collard and Dellas (2002) emphasize an additional mechanism specific to the open economy through which technology shocks may induce short run negative comovements betwen output and labor input even in the absence of nominal rigidities. They analyze an two-country RBC model with imperfect substitutability between domestic and foreign consumption goods. If that substitutability is sufficiently low, a positive technology shock in the home country triggers a large deterioriation in its terms of trade (the price of domestic goods relative to foreign goods). That change in relative prices may induce households to increase their consumption of leisure at any given product wage, thus contracting labor supply and lowering hours. The quantitative analysis of a calibrated version of their model suggests that while technology shocks may be a non-negligible source of output fluctuations its role is likely to be very small as a driving force behind hours fluctuations.

The papers discussed in this section provide examples of model economies which can account for the evidence regarding the effects of technology shocks without relying on any nominal frictions. On the basis of that evidence it is not possible to sort out the relative role played by "nominal" and "real" frictions in accounting for the evidence. The reason is simple: there is no clear mapping between the estimated coefficients in a VARs and the underlying structural parameters which determine the degree of those frictions. As a result the estimated VARs cannot serve as the basis of the sort of counterfactual simulations that would allow us to uncover the implied effects of technology shocks if each of the possible frictions was not present. Such counterfactual exercises require the use of an estimated structural model. In the next section we turn our attention to one such model.

6. Technology Shocks and the Business Cycle in an Estimated DSGE Model

In section 4 we have developed a highly stylized sticky-price model and determined the conditions under which a technology shock could have short run effects consistent with the evidence described in section 2. Furthermore, using a plausible parameter calibration we have concluded that not only those effects were possible, but also quite likely given a realistic description of the monetary policy regime. In section 5 we have discussed alternative explanations for the same evidence, which did not rely on the existence of any nominal frictions, like the presence of habit formation in consumption.

In the present section we try to sort out the merits of the two types of explanations by estimating and analyzing a framework that incorporates both types of frictions, and which is sufficiently rich to be taken to the data. The features that we incorporate include habit formation in consumption, staggered price and wage-setting a la Calvo, flexible indexation of wages and prices to lagged inflation, and a monetary policy rule of the Taylor type with interest rate smoothing.

Several examples of estimated general equilibrium models can be found in the literature.[28] Our framework is most closely related to the one used in Rabanal (2003), with two main differences. First, we allow for a unit root in the technology process in a way consistent with the assumptions underlying the identification strategy pursued in section 2. Second, we ignore the cost channel mechanism allowed for in Rabanal (2003), in light of the evidence in that paper suggesting an insignificant role for that mechanism.

We estimate the parameters of the model using Bayesian methods, and focus our analysis on the implications of the estimated model regarding the effects of technology shocks and the contribution of the latter to the business cycle. The use of a structural estimated model allows us to determine, by means of counterfactual simulations, the role played by different factors in accounting for the estimated effects of technology shocks. Last but not least, the estimated model gives us an indication of the nature of the shocks that have played a dominant role as a source of postwar business cycles.

The use of Bayesian methods to estimate DSGE models has increased over the recent years, in a variety of contexts.[29] Fernández-Villaverde and Rubio-Ramírez (2004) show that parameter estimation is consistent in the Bayesian framework even under model misspecification. Smets and Wouters (2003a, 2003b) estimate a model with capital accumulation, and both nominal and real rigidities for the euro area and the U.S.. Lubik and Schorfheide (2003) use the Bayesian framework to estimate a small scale open economy model. Rabanal (2003) estimates a general equilibrium model for the United States and the euro area in search for cost channel effects of

[28] Prominent examples include Smets and Wouters (2003a, 2003b), Altig et al. (2003), and Ireland (2003).

[29] However, the existing literature on estimating general equiilibrium models using Bayesian methods assumes that all shocks are stationary, even when highly correlated. A novelty of this paper is that we introduce a permanent technology shock. Ireland (2004) estimates a general equilibrium model with permanent technology shocks, using maximum likelihood.

monetary policy.[30]

Next we summarize the set of equilibrium conditions of the model.[31] The demand side of the model is represented by the Euler-like equation

$$b\ \Delta y_t = E_t\{\Delta y_{t+1}\} - (1-b)\ \ (r_t - E_t\{\pi_{t+1}\}) + (1-\rho_g)(1-b)\ g_t \tag{6.1}$$

which modifies equation (4.1) above by allowing for some external habit formation (indexed by parameter b), an introducing a preference shock $\{g_t\}$, that follows an AR(1) process with coefficient ρ_g. Underlying (6.1) there is an assumption that preferences are separable between consumption and hours, and logarithmic in the quasidifference of consumption in order to preserve the balanced growth path property.[32] Aggregate output and hours are related by the simple production function

$$y_t = a_t + n_t$$

Equivalently, and using a tilde to denote variables normalized by current productivity (in order to induce stationarity), we have

$$\tilde{y}_t = n_t \tag{6.2}$$

Log-linearization of the optimal price-setting condition around the zero inflation steady state yields an equation describing the dynamics of inflation as a function of the deviations of the

[30] A somewhat different estimation strategy is the one followed by Christiano, Eichenbaum and Evans (2003), Altig et al. (2003) and Bovin and Giannoni (2003), who estimate general equilibrium models by matching model's implied impulse-response functions to the estimated ones.

[31] Details may be provided in an appendix in the future.

[32] Specifically, the underlying objective function for household j is $E_0 \sum_{t=0}^{\infty} \beta^t [G_t \log(C_t^j - bC_{t-1}) - \frac{(N_t^j)^{1+\varphi}}{1+\varphi}]$. where the preference shock evolves, expressed in logs, as: $g_t = (1-\rho_g)\bar{G} + \rho_g\ g_{t-1} + \varepsilon_t^g$.

average (log) markup from its steady state level, which we denote by μ_t^p.

$$\pi_t = \gamma_b \; \pi_{t-1} + \gamma_f \; E_t\{\pi_{t+1}\} - \kappa_p \; (\mu_t^p - u_t) \tag{6.3}$$

where $\gamma_b = \frac{\eta_p}{1+\beta\eta_p}$, $\gamma_f = \frac{\beta}{1+\beta\eta_p}$, $\kappa_p = \frac{(1-\beta\theta_p)(1-\theta_p)}{\theta_p(1+\eta_p\beta)}$, θ_p is the probability of not adjusting prices in any given period, and $\eta_p \in [0,1]$ is the degree of price indexation to lagged inflation. Notice that $\mu_t^p = -\log\left(\frac{W_t}{P_t A_t}\right) \equiv -\tilde{\omega}_t$ is the price markup, where $\tilde{\omega}_t = \omega_t - a_t$ is the real wage per efficiency unit. We use u_t denote an exogenous shock to the desired price markup.

Log-linearization the optimal wage-setting condition yields the following equation for the dynamics of the (normalized) real wage:

$$\begin{aligned} \tilde{\omega}_t \;\; = \;\; & \frac{1}{1+\beta}\,\tilde{\omega}_{t-1} + \frac{\beta}{1+\beta}\;E_t\{\tilde{\omega}_{t+1}\} - \frac{1}{1+\beta}\Delta a_t + \frac{\beta}{1+\beta}E_t\{\Delta a_{t+1}\} + \frac{\eta_w}{1+\beta}\pi_{t-1} \\ & -\frac{(1+\beta\eta_w)}{1+\beta}\pi_t + \frac{\beta}{1+\beta}E_t\{\pi_{t+1}\} - \frac{\kappa_w}{1+\beta}\;(\mu_t^w - v_t) \end{aligned} \tag{6.4}$$

where θ_w denotes the fraction of workers that do not re-optimize their wage, $\eta_w \in [0,1]$ is the degree of wage indexation to lagged inflation, and where $\kappa_w \equiv \frac{(1-\theta_w)(1-\beta\theta_w)}{\theta_w(1+\epsilon_w\varphi)}$, where ϵ_w is the wage elasticity of labor demand in the steady state. Also notice that $\mu_t^w \equiv \tilde{\omega}_t - (\frac{1}{1-b}\tilde{y}_t - \frac{b}{1-b}\tilde{y}_{t-1} - g_t + \frac{b}{1-b}\Delta a_t + \varphi n_t)$ is the wage markup. We use v_t denote an exogenous shock to the desired wage markup.

Finally, to close the model, we assume that the monetary policy rule reacts to inflation and to output growth with interest rate smoothing:

$$r_t = \phi_r \; r_{t-1} + (1-\phi_r)\phi_\pi \; \pi_t + (1-\phi_r)\phi_y \; \Delta y_t + z_t \tag{6.5}$$

where z_t is an exogenous monetary shock.

Following Erceg and Levin (2003), we assume that the Federal Reserve reacts to output growth rather than the output gap. An advantage of following such a rule, as Orphanides and Williams (2002) stress, is that mismeasurement of the level of potential output does not affect the conduct of monetary policy (as opposed to using some measure of detrended output to estimate the output gap).

The exogenous driving variables are assumed to evolve as follows:

$$\begin{aligned}
a_t &= a_{t-1} + \varepsilon_t^a \\
g_t &= \rho_g \; g_{t-1} + \varepsilon_t^g \\
u_t &= \rho_u \; u_{t-1} + \varepsilon_t^u \\
v_t &= \rho_v \; v_{t-1} + \varepsilon_t^v \\
z_t &= \varepsilon_t^z
\end{aligned}$$

Notice that while we do not observe $\tilde{\omega}_t$ and $\tilde{y}_t$, the two variables are related as follows:

$$\omega_t - y_t = \tilde{\omega}_t - \tilde{y}_t$$

and $\omega_t - y_t$ is an observable variable, which should be stationary in equilibrium. In the next section, we explain how to write the likelihood function in terms of the five observable variables:

output growth, inflation, the nominal interest rate, hours, and the real wage-output ratio.

6.1. Parameter Estimation

6.1.1. The Data

We estimate the model laid out in the previous section using U.S. quarterly time series for five variables: real output, inflation, real wages, hours and interest rates. The sample period is 1948:01 to 2002:04. For consistence with the analysis in section 2, we use the same series for output and hours. Our measure of nominal wages is the compensation per hour in the nonfarm business sector (LXNFC), and the measure for the price level is the nonfarm business sector deflator (LXNFI). Finally, we use the quarterly average daily readings of the 3-month T-bill (FTB3) as the relevant nominal interest rate. In order to render them stationary we detrend hours and the real wage-output ratio using a quadratic trend. We treat inflation, output growth and the nominal interest rate as stationary, and express them in deviations from their sample mean.

As is well know from Bayes' rule, the posterior distribution of the parameters is proportional to the product of the prior distribution of the parameters and the likelihood function of the data. Until recently, only well known and standard distributions could be used. The advent of fast computer processors and Markov Chain Monte Carlo (MCMC) methods has removed this restriction, and a more general class of models and distributions can be used.[33] In order to implement the Bayesian estimation method, we need to be able to evaluate numerically the prior and the likelihood function. Then, we use the Metropolis-Hastings algorithm to obtain random draws from the posterior distribution, from which we obtain the relevant moments of

[33] See Fernández-Villaverde and Rubio-Ramírez (2004).

the posterior distribution of the parameters.

6.1.2. The Likelihood Function

Let ψ denote the vector of parameters that describe preferences, technology, the monetary policy rule and the shocks of the model, d_t be the vector of endogenous variables (observable or not), z_t be the vector of shocks, and ε_t be the vector of innovations.

The system of equilibrium conditions and the process for the exogenous shocks can be written as a second order difference equation

$$A(\psi) \;\; E_t\{d_{t+1}\} = B(\psi) \;\; d_t + C(\psi) \;\; d_{t-1} + D(\psi) \;\; z_t,$$

$$z_t = N(\psi) \;\; z_{t-1} + \varepsilon_t, \quad E(\varepsilon_t \varepsilon_t') = \Sigma(\psi).$$

We use standard solution methods for linear models with rational expectations (see, e.g., Uhlig, (1999)) to write the law of motion in state-space form and the Kalman filter, as in Hamilton (1994) to evaluate the likelihood of the five observable variables $x_t = (r_t, \pi_t, \omega_t - y_t, n_t, \Delta y_t)'$. We denote by $L\left(\{x_t\}_{t=1}^{T} | \psi\right)$ the likelihood function of $\{x_t\}_{t=1}^{T}$.

6.1.3. Priors

In this section, we denote by $\Pi(\psi)$ the prior distribution of the parameters. We present the list of the structural parameters and its associated prior distributions in Table 4. Most of the priors involve uniform distributions for the parameters, which simply restrict the support. We use uniform distributions for the parameter that explains habit formation, for the probabilities of the Calvo lotteries, and for the indexation parameters. The probabilities of the Calvo lottery are allowed to take values up to 0.9, i.e., we are ruling out average price and wage durations of more than 10 quarters. The elasticities of the interest rate rule to inflation and output fluctuations, and the φ parameter have normal prior distributions. They are conveniently trucated to the region where the model has a stable and unique solution.

We try to supplement as much prior information as possible for the model's exogenous shocks. The AR(1) coefficients have uniform prior distributions between 0 and 0.97. Gamma distributions for the standard deviations of the shocks are assumed, to stay in positive reals, and we select their hyperparameters to match available information for the prior mean standard deviation of the innovations, while allowing reasonable uncertainty in this parameters. For instance, for the monetary shock, we use the standard deviation that comes from running an OLS regression for the Taylor rule equation.

In addition, we fix the following parameters: for the discount factor, we set $\beta = 0.99$. The elasticities of product and labor demand are set to 6 (which implying steady state markups of 20 percent). These values are pretty conventional in the literature.

6.1.4. Drawing from the Posterior

From Bayes rule, we obtain the posterior distribution of the parameters as follows:

$$p(\psi|\,\{x_t\}_{t=1}^{T}) \propto L(\{x_t\}_{t=1}^{T}\,|\psi)\;\Pi\,(\psi)$$

The posterior density function is proportional to the product of the likelihood function and the prior joint density function of ψ. Given our priors and the likelihood functions implied by the state-space solution to the model, we are not able to obtain a closed-form solution for the posterior distributions. However, we are able to evaluate both expressions numerically. We follow Fernández-Villaverde and Rubio-Ramírez (2004) and Lubik and Schorfheide (2003) and use the random walk Metropolis-Hastings algorithm, to obtain a random draw of size 500,000 from $p\left(\psi|\left\{x_t\right\}_{t=1}^{T},m\right)$. We use the draw to estimate the moments of the posterior distribution, and to obtain impulse responses and second moments of the endogenous variables.

6.2. Main Findings

6.2.1. Second Moments

Table 5 presents the posterior distributions of the parameters. The first two columns of the table present the mean and the standard deviation of the parameters for the full sample. The habit formation parameter is estimated to be 0.42, a value somewhat smaller than that suggested by Christiano, Eichenbaum and Evans (2003) or Smets and Wouters (2003b). This could be due to the fact that our model already incorporates a nonstationary process, making the need for persistence via habit formation less important. The parameter that measures the elasticity of the marginal disutility of hours, φ, is estimated to be 0.80, which is close to values usually obtained or calibrated in the macroeconomic literature.

The average duration of price contracts lies slightly above two quarters, the point estimate is 2.11. We view this estimate as a "moderate" amount of price stickiness in the economy. The most surprising result of the estimation is the low average duration of wage resetting, 1.08 periods. By no means we are trying to suggest that wages are flexible, but this might be signalling that the Calvo model is not the best formalism to characterize wage dynamics. An explanation of this result is that the degree of habit formation in consumption induces persistence in the marginal rate of subtitution between consumption and hours, and this is enough to obtain sticky real wages, which is what we observe in the data.[34]

The price indexation coefficient is estimated at a low value, 0.04, suggesting that the pure forward looking model is a good aproximation to inflation dynamics, once we allow for autorregressive price mark up shocks. On the other hand, indexation in wage setting is more important, with a posterior mean of 0.42. The coefficients of the interest rate rule suggest a high degree of interest rate smoothing, 0.69, a small response of the interest rate to output growth fluctuations, and a coefficient of the response of the interest rate to inflation of 1.33, which corresponds to a "lean against the wind" monetary policy, or, what is the same, that respects the Taylor principle. The estimated values for the shocks of the model suggest that all of them are highly correlated, with parameters between 0.95 for the price markup shock to 0.91 for the wage markup shock.

The next two columns of Table 5 report subsample estimates. The first subsample period corresponds to the pre-Volcker years (1948:1-1979:4). The second comprises the Volcker-Greenspan era (1982:04-2002:04), starting after the brief experiment with nonborrowed reserves targeting. There are no important differences in the estimation. We find a smaller degree of habit formation in consumption, of just 0.26, and a smaller coefficient on interest rate smoothing in the latter period. On the other hand, both monetary and technology shocks have large standard deviations, and all the other shocks exhibit either the same or larger autorregressive coefficients. The estimates for the 1982:04-2003:03 period suggest a slightly higher degree of price rigidity, since the estimate increases to 3.15 quarters. We also a detect a higher interest rate response in the Volcker-Greenspan Fed to changes in the inflation rate, but the difference does not appear to be significant, in contrast with some of the existing literature.

[34] Rabanal (2003) finds the same result estimating a similar model as the one presented here, using data for the United States and the euro area.

In Table 6, we present selected posterior second moments of the model, and compare them to the data.[35] The first two columns present the standard deviation of the observed variables, and their counterparts implied by the estimated the model. We can see that the model does a very good job in replicating the standard deviations of output, inflation and the nominal interest rate. The model also does a great job in mimicking the unconditional correlation between the growth rates of hours and output: in the data it is 0.75, and in the model it is 0.72. However, it overestimates the standard deviation of hours, which is 3.11 percent in the data and 4.6 percent in the model, and to a lesser extent the real wage-to-output ratio, which is 3.69 percent in the data and 4.44 percent in the model.

6.2.2. The Effects of Technology Shocks

Next we turn our attention to the estimated model's predictions regarding the effects of technology shocks. Figure 7 displays the posterior impulse responses to a permanent one standard deviation technology shock.[36] We can observe that the model replicates the VAR-based evidence fairly well, in spite of the differences in the approach. In particular the estimated model implies a persistence decline in hours in response to a positive technology shock, and a gradual adjustment of output to its permanently higher plateau. It takes about four quarters for output to go to its new steady state level, and, as a result, hours drop in impact about 0.4 percentage points deviation from their steady state value, and converge monotonically afterwards.[37]

The third column of Table 6 reports the second moments of the observed variables conditional

[35] These second moments where obtained using a sample of 10,000 draws from the 500,000 that were previously obtained with the Metropolis-Hastings algorithm.

[36] The posterior mean and standard deviations are based on a sample of 10,000 draws from the 500,000 draws obtained from the Metropolis-Hastings algorithm.

[37] A similar pattern of responses of output and hours to a technology shocks can be found in Smets and Wouters (2003b), using a model with capital accumulation..

on technology shocks being the only driving force. The fourth column shows the fraction of the variance of each variable accounted for by the technology shock. We can see that technology shocks do not play a major role in explaining the variability of the five observed variables. They explain 22 percent of the variability of output growth, and 6 percent of the variability of inflation. For the rest of variables, including hours, they explain an insignificant amount of overall volatility.[38] A key result emerges when we simulate the model with technology shocks only: we obtain a correlation between $(\Delta y_t, \Delta n_t)$ of -0.49, which contrasts with the high positive correlation between the same variables observed in the data.

The last three rows of Table 6 report similar statistics based on band-pass filtered data. In this case, the series of output growth and hours that come from the model are used to obtain the levels of (log) hours and output, and the band-pass filter is applied. In order to extract the technology shock, we use the method of Ingram, Kocherlakota and Savin (1994) to obtain the structural shocks.[39] By construction, the shocks replicate perfectly the features of the model. However, when we simulate the model with technology shocks only, we finds that they explain small fractions of the variance of the business cycle component of output and hours. The conditional correlation between those two variables falls to -0.14, from a value of 0.88 for the actual filtered series.

The previous results are illustrated graphically in Figures 7 and 8. Figure 7 displays the historical series for output growth and hours with all the shocks at work and with the technology shocks only. Figure 8 presents the same exercise with band-pass filtered data. In both cases, it

[38] We also estimated a model with the following process for technology: $\Delta a_t = \rho_a \Delta a_{t-1} + \varepsilon_t^a$, and the posterior mean for the autorregresive component was 0.05. Therefore, results do not change significantly with this specification.

[39] This method is a particular case of using the Kalman filter to obtain the strucutural shocks. It assumes that the economy is at its steady state value in the first observation, rather than assuming a diffuse prior.

becomes clear that technology shocks only explain a minor fraction of fluctuations. This is even more dramatic when we look at fluctuations in hours, in a way consistent with most of the VAR findings. Similar qualitative findings are found in Altig et al. (2003), Ireland (2003) and Smets and Wouters (2003b).

In Table 8 we report the implied second moments for each of the subsample periods. For the 1948-1979 period, we can see that the model again matches the standard deviation of output growth, inflation and nominal interest rates fairly accurately, but overestimates that of hours and the real wage-output ratio. Interestingly, technology shocks play a larger role in explaining the variability of output growth, since roughly one third of the variance in the earlier period can be explained by technology shocks only. The model is also able to replicate the correlation between $(\Delta y_t, \Delta n_t)$, which is 0.75 in the data and 0.73 in the model. But when only technology shocks are used, then the correlation becomes large and negative, -0.63. In the 1982-2002 period, the model seems to explain better the standard deviation of the five variables, since the model-based second moments of hours and the real wage-to-output ratio are not that far off. Once again, the models mimick the correlation between the first difference of hours and output fairly well, which turns negative (-0.42) with technology shocks only. With respect to the previous subsample, technology shocks explain a smaller fraction of output growth variance, but a higher fraction of inflation variance. The contribution to the variance of the remaining variables is always very small in the two subsamples.

6.2.3. What are the Main Sources of Economic Fluctuations?

Which shocks explain the business cycle volatility of the set of observable variables? In Table 8, we present the contribution of each shock to the total variance of each variable for the entire sample. The shock that explains most of the variance of all variables in our framework is the preference shock. It explains above 70 percent of the variance of hours, the real wage-to-output ratio, and the nominal interest rate. The preference shock also explains 57 percent of the variance of output, and 36 percent of the variance of inflation. On the other hand, the monetary shock only explains approximately 5 percent of output growth and the nominal interest rate, and is an important determinant of inflation variability, contributing to 27 percent of total volatility. Price and wage mark up shocks both have some importance in explaining the volatility of all variables, with contributions to the variance that range from 7 percent to 17 percent. So the picture that emerges from Table 6 is that preference shocks are key to explain the volatility of all variables. The monetary and technology shocks have some importance in the sense that they explain about 20 percent of the variance in one of the variables (output growth in the case of technology, inflation in the case of monetary shocks), but their contribution to the remaining variables is very small. The price and wage markup shocks explain a small fraction of variability in all variables.

6.2.4. Structural Explanations for the Estimated Effects of Technology Shocks

Finally, we examine which features of the model are driving the negative comovement between hours and output in response to technology shocks. In Table 9 we present the correlation between $(\Delta y_t, \Delta n_t)$ that arises under several counterfactual scenarios. For each scenario we shut down some of the rigidities of the model and simulate it again while keeping the same value for the remaining parameter estimates.

Three features of the model stand out as natural candidates to explain the negative correlation between output and hours: sticky prices, sticky wages, or habit formation. When we shut down each of those of those we find that the remaining rigidities still induce a large and negative conditional correlation. For instance, in the second row we can see that assuming flexible wages ($\theta_w = \eta_w = 0$) delivers basically the same correlations. This result is not surprising given that nominal wage rigidities do not appear to be important given the parameter estimates. When we assume flexible prices but keep sticky wages and habit formation, things do not change much either.

A particular scenario would seem to be of special interest, namely, the one with flexible prices and wages, and habit formation. In that case, once again, a similar pattern of correlations emerges. A similar result is obtained by Smets and Wouters (2003b), who interpret it as evidence favorable to some of the real explanations found in the literature.

Yet, when we turn off habit formation in our estimated model but keep nominal rigidities we find a qualitatively similar result: the conditional and unconditional correlations between hours and output have the same pattern of signs as that observed in the data.

It is only when we shut down all rigidities (nominal and real) that we obtain a positive correlation between hours and output, both conditionally and unconditionally, and in a way consistent with the predictions of the basic RBC model.

Finally, we consider a calibration in which the central bank responds exclusively to inflation changes, but not to output. Some authors have argued that the negative comovement of output and hours may be a consequence of an attempt by the monetary authority to overstabilize output. Our results suggest that this cannot be an overriding factor: when we set the coefficient on output growth equal to zero (and keep both habit formation and nominal rigidities operative) we still obtain a negative conditional correlation between hours and output.

In light of the previous findings we conclude that both real rigidities (habit formation) and nominal rigidities (mostly sticky prices) appear to be relevant factors in accounting for the evidence on the effects of technology shocks. Interestingly, *both* nominal and real rigidities seem to be required in order to account for the empirical effects of monetary policy shocks (see e.g. Christiano, Eichenbaum and Evans (1999)) or the dynamics of inflation (e.g., Galí and Gertler (1999)).

7. Conclusions

[INCOMPLETE]

In the present paper we have reviewed recent research efforts that seek to identify and estimate the role of technology as a source of economic fluctuations in ways that go beyond the simple unconditional second moment matching exercises found in the early RBC literature. The number of qualifications and caveats of any empirical exercise that seeks to provide an answer to the above questions is never small. Furthermore, and as is often the case in empirical research in economics, the evidence does not speak with a single voice, even when similar methods and data sets are used. That notwithstanding, the bulk of the evidence reported in the present paper raises serious doubts about the importance of changes in aggregate technology as a significant (or, even more, a dominant) force behind business cycles, in contrast with the original claims of the RBC literature. Instead it points to demand factors as the main force behind the strong positive comovement between output nd labor input measures that is the hallmark of the business cycle.

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TABLE 1.

The Effects of Technology Shocks on Output and Hours in the Nonfarm Business Sector

	Contribution to:		Conditional	Impact on *n* and *y*:	
	var(y)	var(n)	corr(y,n)	sign	significance
Per Capita Hours					
Difference	0.07	0.05	-0.08	- / +	yes / yes
Level	0.37	0.11	0.80	+ / +	no / yes
Detrended	0.07	0.05	-0.11	- / +	yes / yes
Total Hours					
Difference	0.06	0.06	-0.03	- / +	yes / yes
Level	0.10	0.36	0.80	- / -	yes / no
Detrended	0.15	0.36	0.80	- / 0	yes / no

TABLE 2. The Effects of Technology Shocks on GDP and Employment

	Contribution to:		Conditional	Impact on *n* and *y*:	
	var(y)	var(n)	corr(y,n)	sign	significance
Employment Rate					
Difference	0.31	0.04	0.40	- / +	yes / yes
Level	0.03	0.19	-0.30	- / +	yes / no
Detrended	0.15	0.04	-0.43	- / +	yes / yes
Total Employment					
Difference	0.21	0.03	-0.40	- / +	yes / yes
Level	0.09	0.08	-0.72	- / +	yes / yes
Detrended	0.09	0.09	-0.68	- / +	yes / no

TABLE 3. Investment-Specific Technology Shocks: The Fisher Model

	N-Shocks			I-Shocks		
	Contribution to:			Contribution to:		
	var(y)	var(n)	corr(y,n)	var(y)	var(n)	corr(y,n)
Per Capita Hours						
Difference	0.06	0.06	-0.09	0.22	0.19	0.94
Level	0.12	0.02	0.16	0.62	0.60	0.96
Detrended	0.08	0.07	-0.03	0.10	0.09	0.94
Total Hours						
Difference	0.07	0.06	0.05	0.16	0.14	0.94
Level	0.05	0.15	0.33	0.82	0.78	0.97
Detrended	0.10	0.28	0.62	0.09	0.08	0.93
Employment Rate						
Difference	0.21	0.05	0.08	0.19	0.13	0.93
Level	0.08	0.08	-0.32	0.86	0.89	0.95
Detrended	0.06	0.17	-0.11	0.12	0.10	0.92
Total Employment						
Difference	0.19	0.06	-0.05	0.10	0.06	0.90
Level	0.04	0.16	-0.25	0.64	0.52	0.96
Detrended	0.04	0.20	0.05	0.12	0.09	0.90

Table 4. Prior Distributions

Parameter		*Std. Dev.*	*Mean*
b	Uniform(0,1)	0.50	0.289
φ	Normal(1,0.25)	1.00	0.25
θ_p	Uniform(0,1)	0.50	0.289
θ_w	Uniform(0,1)	0.50	0.289
η_p	Uniform(0,1)	0.50	0.289
η_w	Uniform(0,1)	0.50	0.289
ρ_r	Uniform(0,0.97)	0.485	0.284
ϕ_y	Normal(0.5,.125)	0.50	0.13
ϕ_π	Normal(1.5,0.25)	1.50	0.25
ρ_g	Uniform(0,0.97)	0.485	0.284
ρ_u	Uniform(0,0.97)	0.485	0.284
ρ_v	Uniform(0,0.97)	0.485	0.284
σ_z	Gamma(25,0.0001)	0.0025	0.0005
σ_a	Gamma(25,0.0004)	0.01	0.002
σ_g	Gamma(16,0.00125)	0.02	0.005
σ_u	Gamma(4,0.0025)	0.01	0.005
σ_v	Gamma(4,0.0025)	0.01	0.005

Table 5. Posterior Distribution of the Model's Parameters

	1947:01-2002:04		1947:01-1979:04		1982:04-2002:04	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
b	0.42	0.04	0.26	0.09	0.51	0.06
φ	0.80	0.11	0.72	0.13	0.56	0.16
θ_p	0.53	0.03	0.31	0.11	0.68	0.04
θ_w	0.05	0.02	0.01	0.01	0.04	0.02
η_p	0.02	0.02	0.09	0.08	0.04	0.04
η_w	0.42	0.28	0.46	0.14	0.41	0.24
ρ_r	0.69	0.04	0.53	0.13	0.72	0.05
ϕ_y	0.26	0.06	0.16	0.06	0.55	0.10
ϕ_π	1.35	0.13	1.34	0.10	1.53	0.22
ρ_g	0.93	0.02	0.96	0.01	0.91	0.03
ρ_u	0.95	0.02	0.96	0.05	0.93	0.04
ρ_v	0.91	0.01	0.91	0.01	0.93	0.02
σ_z	0.003	0.000	0.005	0.001	0.002	0.000
σ_a	0.009	0.001	0.011	0.001	0.007	0.001
σ_g	0.025	0.0024	0.022	0.0026	0.018	0.0029
σ_u	0.011	0.001	0.010	0.001	0.009	0.001
σ_v	0.012	0.001	0.008	0.001	0.008	0.001
Duration Prices	2.11	0.15	1.48	0.23	3.15	0.41
Duration Wages	1.05	0.01	1.01	0.01	1.03	0.02

Table 6. Second Moments of Estimated Dynamic General Equilibrium Model

Original Data				
Standard Deviations	Data	Model	Technology Only	Variance share
Output Growth	1.36%	1.27%	0.60 %	22.3 %
Inflation	0.72%	0.73%	0.18%	6.0 %
Nom. Interest Rate	0.72%	0.67%	0.04%	0.3 %
Hours	3.11%	4.60%	0.42%	0.8 %
Real Wage/Output	3.69%	4.44%	0.13%	0.1 %
Correlation between (dy,dn)	0.75	0.72	-0.49	
Band-Pass Filtered Data				
Standard Deviations				
Output	2.04%	2.04%	0.87%	18.2 %
Hours	1.69%	1.69%	0.26%	2.3 %
Correlation between (y,n)	0.88	0.88	-0.14	

Table 7. Second Moments of Estimated Dynamic General Equilibrium Model

Subsample Analysis

	1948:01 1979:04				1982:04 2002:04			
Original Data								
Standard Deviations	Data	Model	Tech. Only	Variance share	Data	Model	Tech Only	Variance share
Output Growth	1.55%	1.55%	0.92%	35.23%	0.83%	0.84%	0.36%	18.37%
Inflation	0.80%	0.77%	0.14%	3.31%	0.50%	0.45%	0.15%	11.11%
Nom. Interest Rate	0.57%	0.55%	0.05%	0.83%	0.29%	0.43%	0.02%	0.22%
Hours	3.25%	4.86%	0.15%	0.10%	2.84%	3.40%	0.52%	2.34%
Real Wage/Output	3.69%	4.60%	0.10%	0.05%	3.80%	3.24%	0.12%	0.14%
Correlation between (dy,dn)	0.75	0.73	-0.63		0.65	0.66	-0.42	
Band-Pass Filtered Data								
Standard Deviations								
Output	2.28%	2.28%	0.99%	18.85%	1.65%	1.65%	0.66%	16.00%
Hours	1.86%	1.86%	0.29%	2.43%	1.44%	1.44%	0.19%	1.74%
Correlation between (y,n)	0.87	0.87	-0.13		0.90	0.90	-0.15	

Table 8. Contributions of each Shock to Total Variance

	Shocks				
	Monetary	Technology	Preference	Price Markup	Wage Markup
Output Growth	4.8 %	22.3 %	57.1 %	8.0 %	7.1 %
Inflation	27.1 %	6.1 %	36.3 %	13.7 %	14.7 %
Nominal Rate	5.0 %	0.4 %	72.3 %	9.8 %	11.8 %
Hours	0.4 %	0.8 %	70.0 %	17.6 %	9.6 %
Wage - Output	0.1 %	0.1 %	73.6 %	12.0 %	12.8 %

Table 9: Counterfactual correlations between $(\Delta y_t, \Delta n_t)$

	Model	Technology Shocks Only
Original Specification	0.72	-0.49
Flexible Wages	0.72	-0.50
Flexible Prices	0.76	-0.54
No habit formation	0.87	-0.73
Flexible Prices and Wages	0.76	-0.60
Flexible Prices, Wages and no Habit formation	0.87	0.71
Strict Inflation Targeting	0.74	-0.53

Figure 1. Business Cycle Fluctuations in Output and Hours

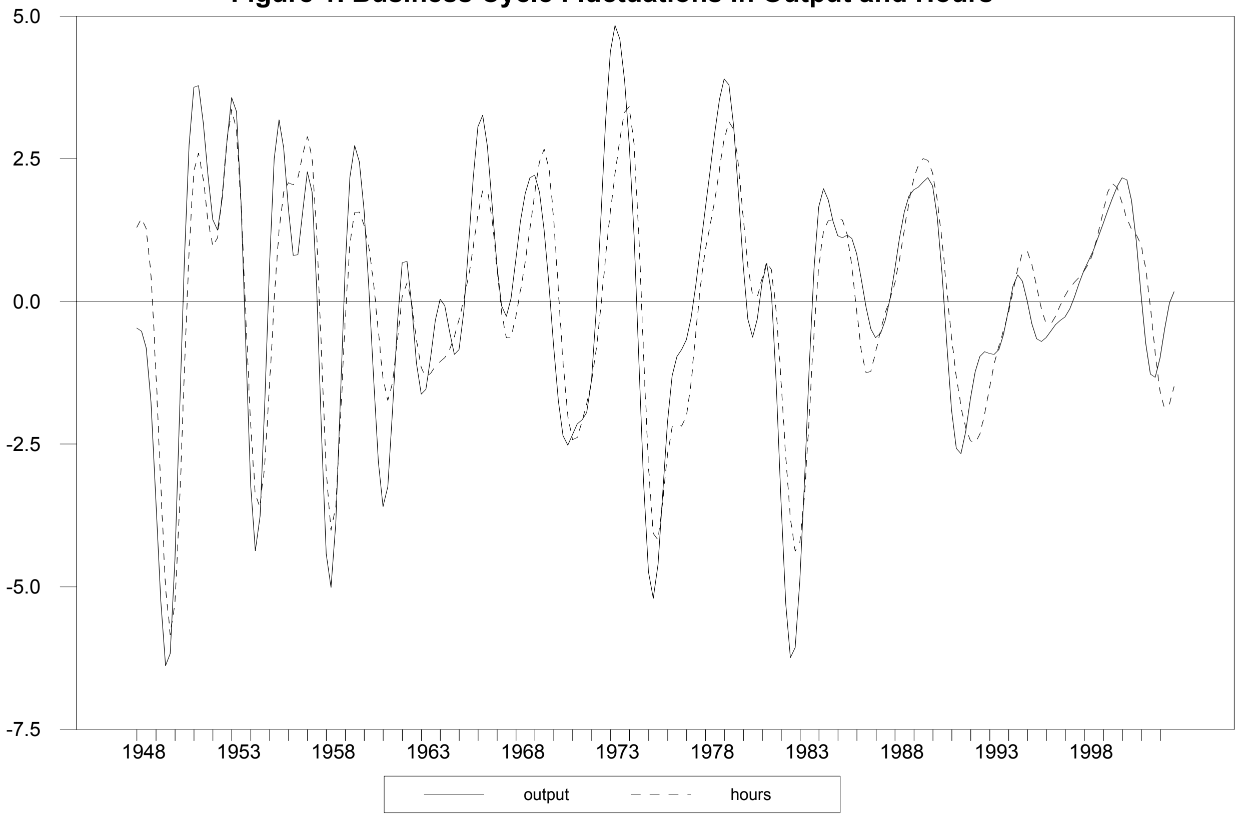

Figure 2. The Estimated Effects of Technology Shocks

Difference Specification , 1948:01-2002:04

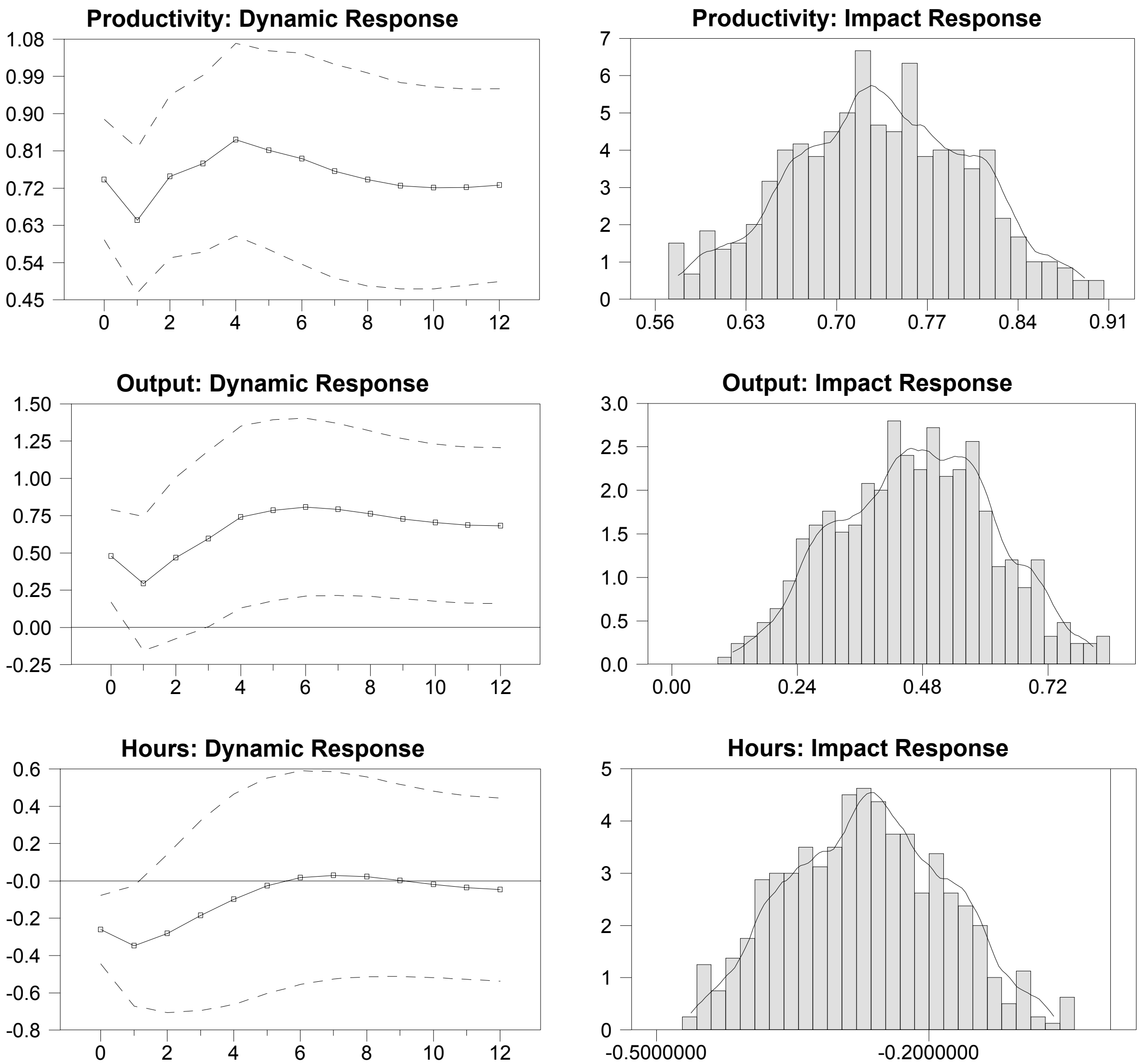

Figure 3: Sources of U.S. Business Cycle Fluctuations

Difference Specification , Sample Period:1948:01-2002:04

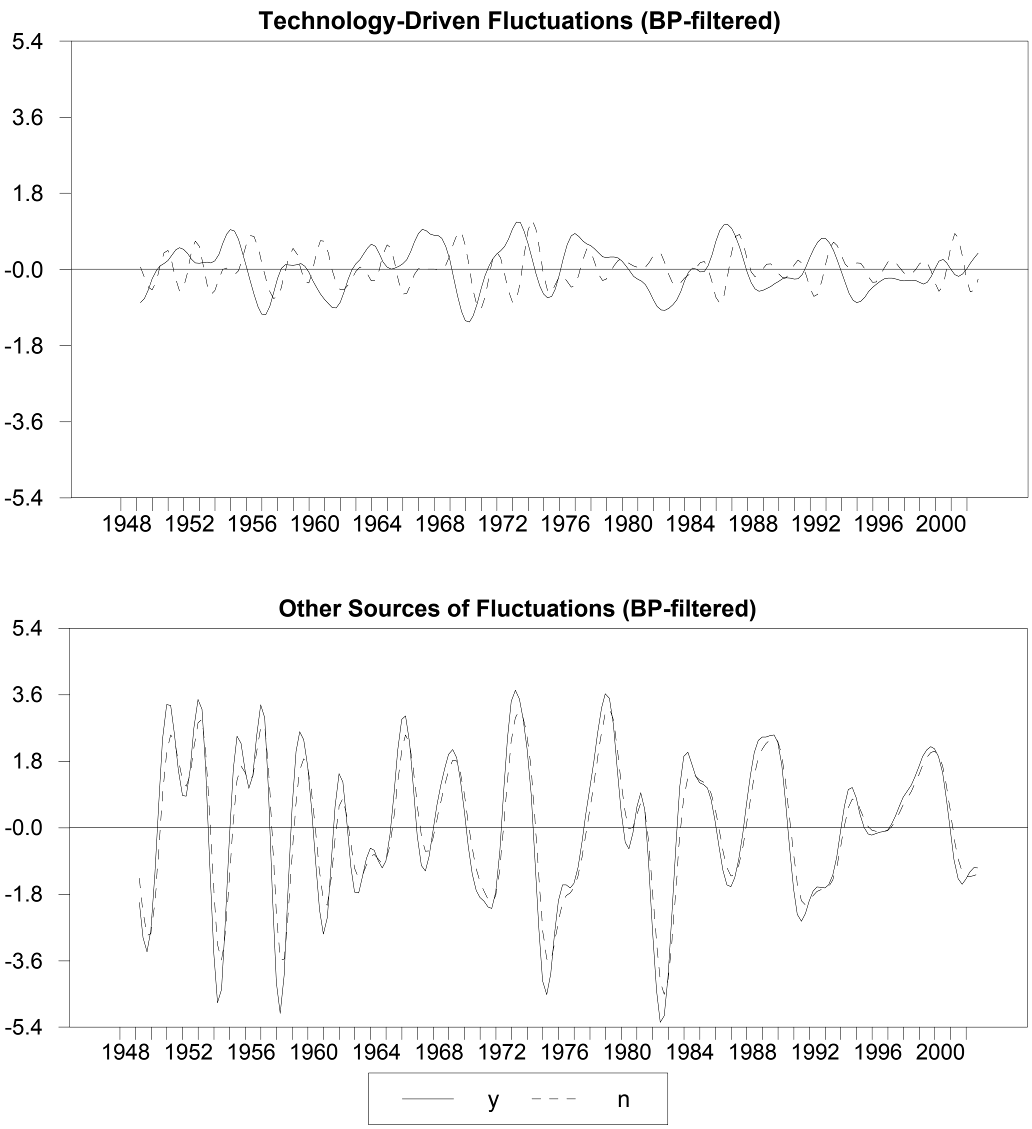

Figure 4: Capital Income Tax Rates

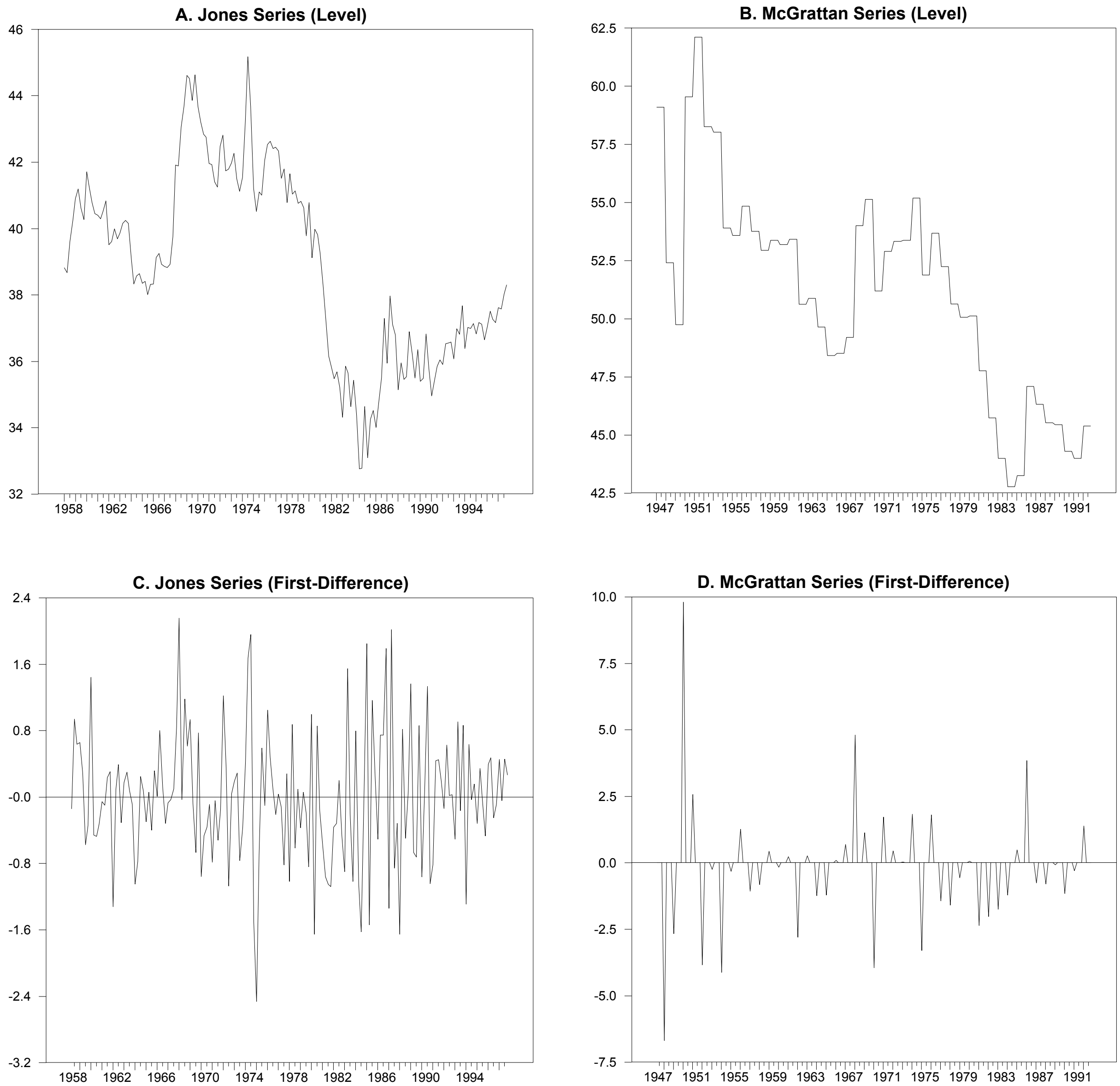

Figure 5. Technology Shocks: VAR vs. BFK

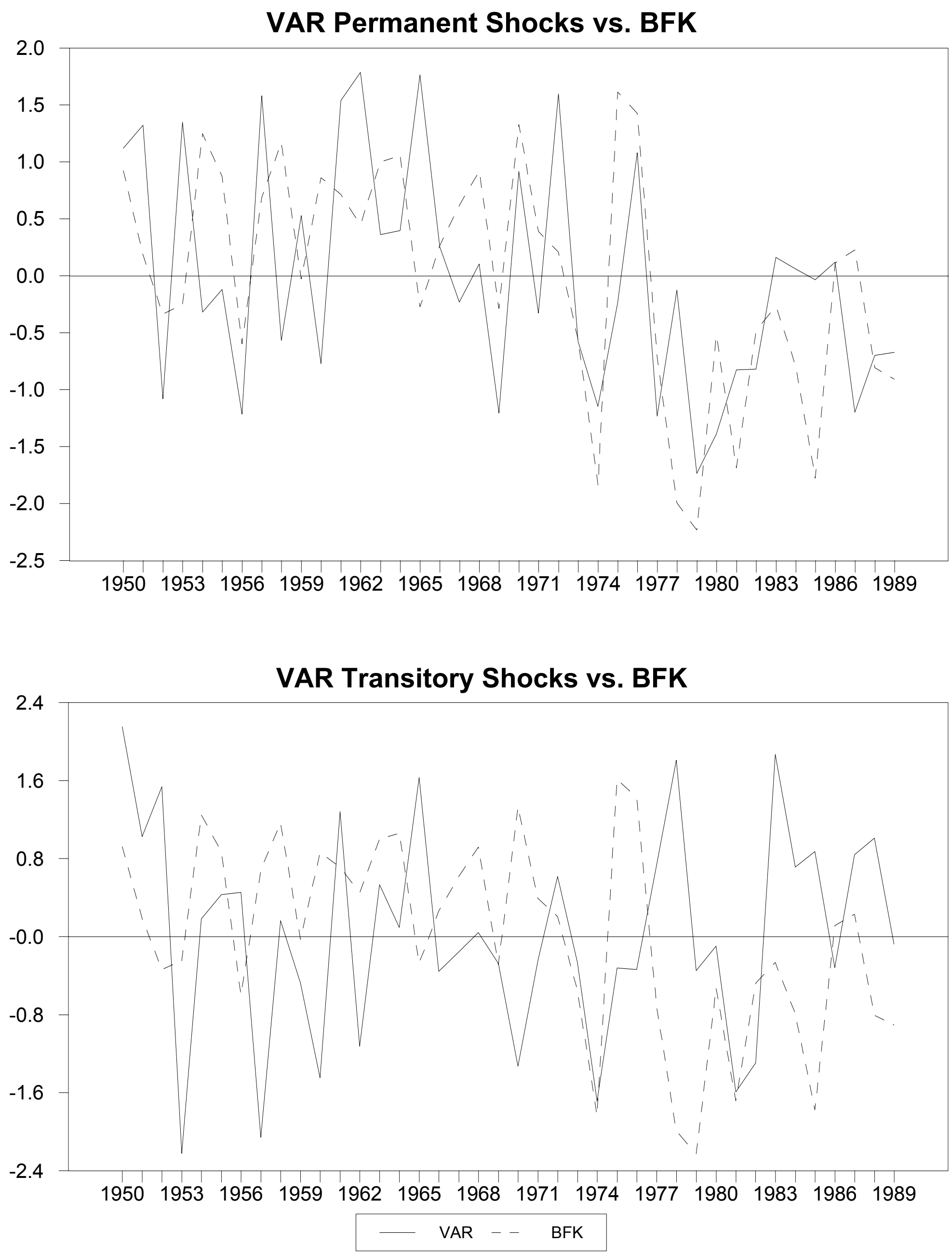

Figure 6. Hours Worked, 1948-2002

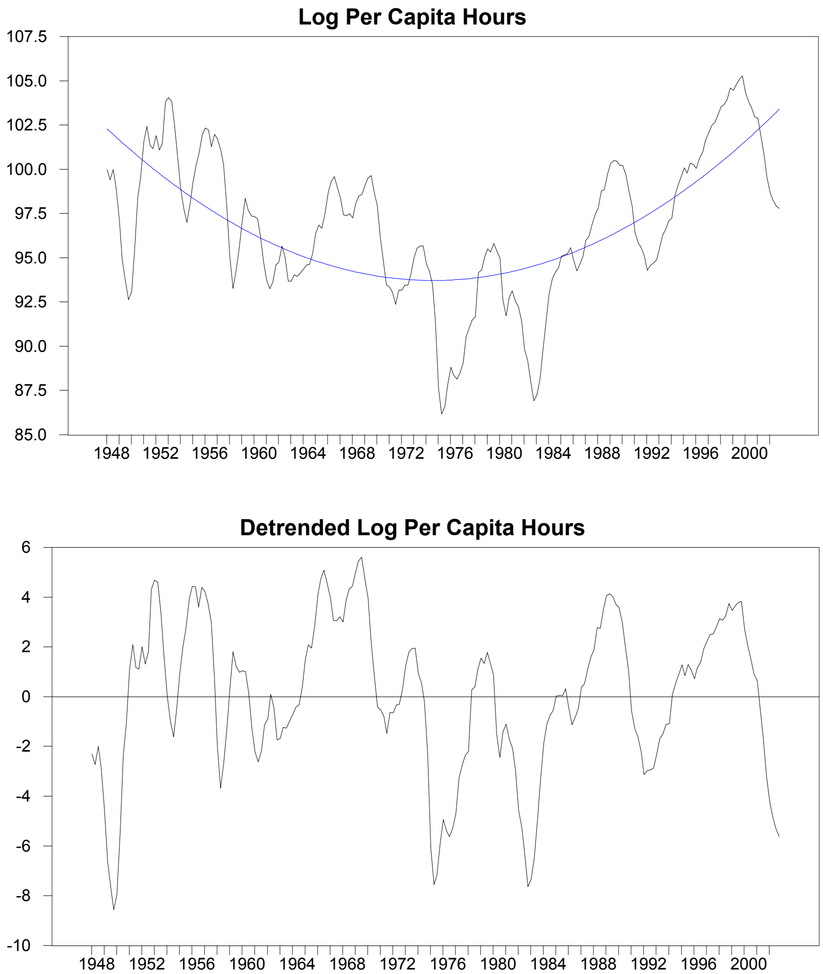

Figure 7. Posterior Impulse Responses to a Technology Shock, Estimated DSGE model

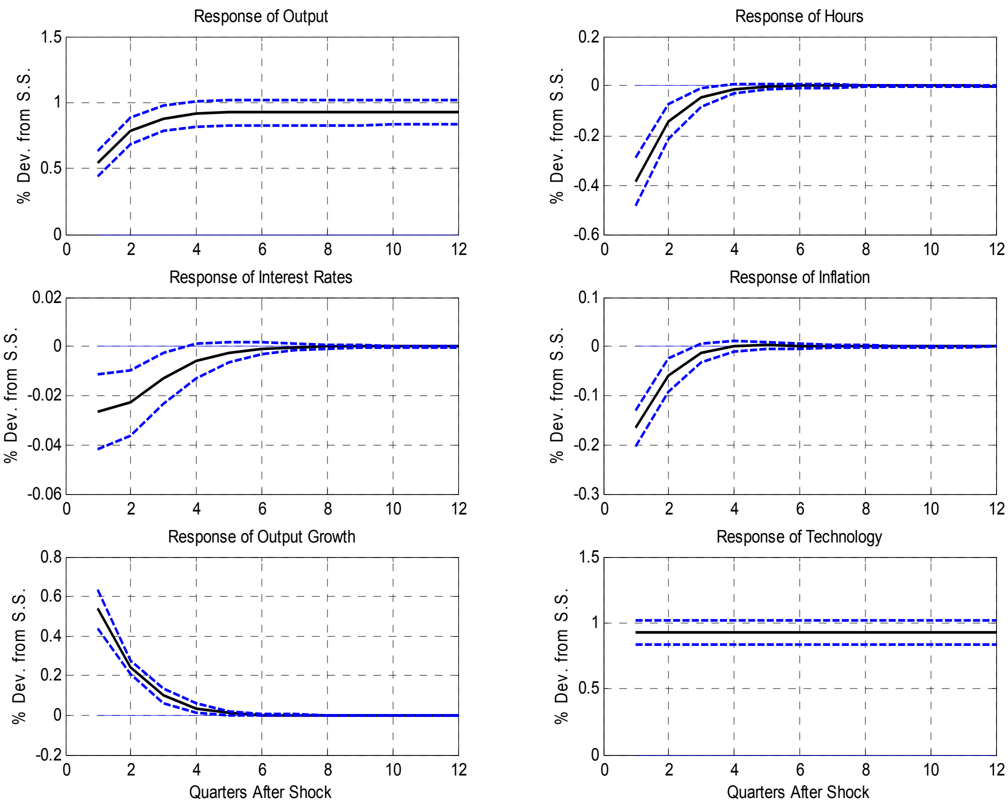

Figure 8. Output Growth and Hours, Original data

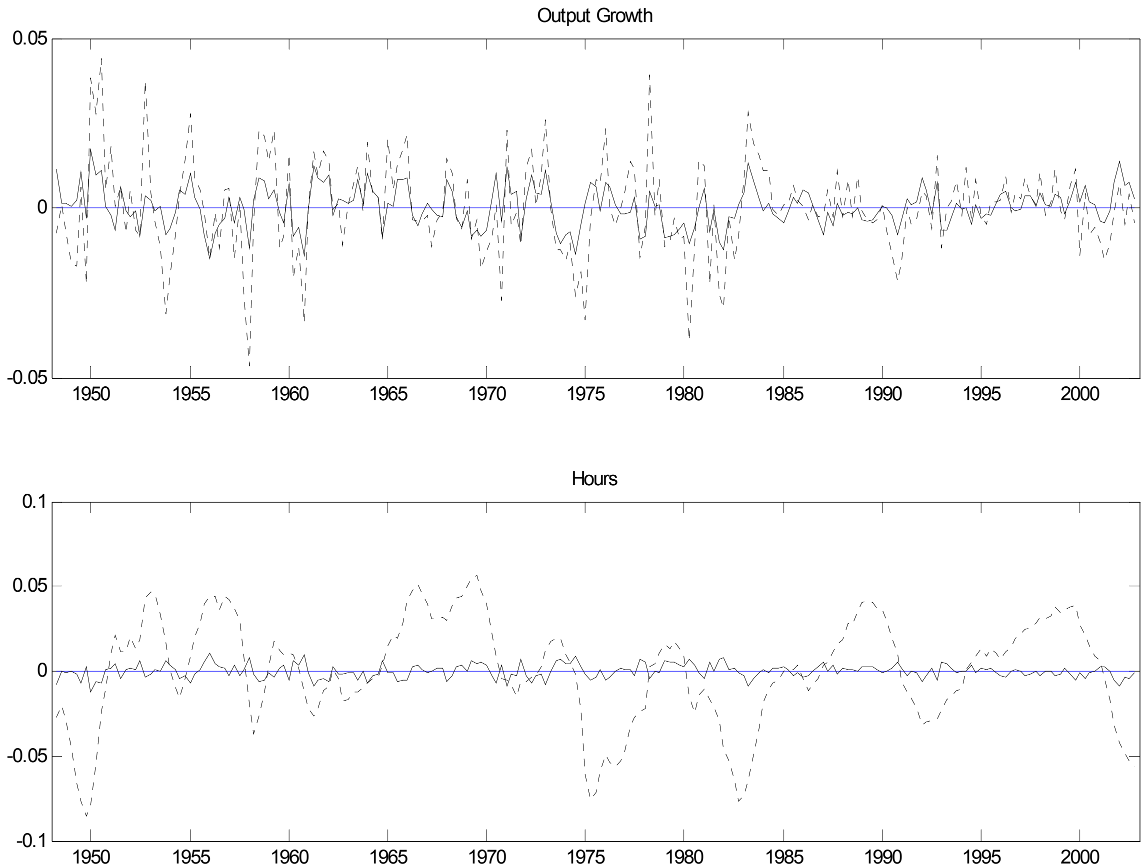

Figure 9. Output and Hours, Band Pass Filtered