

# **Technology Shocks and Aggregate Fluctuations: How Well Does the Real Business Cycle Model Fit Postwar U.S. Data?**

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## **1. Introduction**

Since the seminal work of Kydland and Prescott (1982) and Prescott (1986b), 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 industrialized economies. Those fluctuations have been interpreted by RBC economists as the equilibrium 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 of the most revolutionary 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, seems to account for the bulk of economic fluctuations in the postwar U.S. economy. 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.”<sup>1</sup> Similarly, in two recent assessments of the road traveled and the lessons learned by RBC theory after more than a decade, Cooley and Prescott (1995) could confidently claim that “it makes sense to think of fluctuations as caused by shocks to productivity,” while King and Rebelo (1999) concluded that “[the] main criticisms

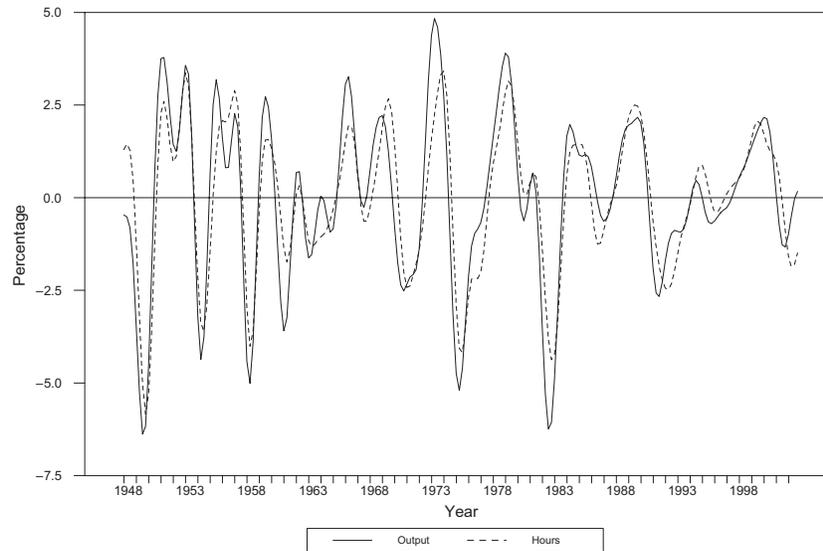
levied against first-generation real business cycle models have been largely overcome.”

While most macroeconomists have recognized the methodological impact of the RBC research program and have adopted its modeling tools, other important, more substantive elements of that program have been challenged in recent years. First, and in accordance with the widely acknowledged importance of monetary policy in industrialized economies, the bulk of the profession has gradually moved away from real models (or their near-equivalent frictionless monetary models) when trying to understand short-run macroeconomic phenomena. Second, and most important 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 focus on the latter development by providing an overview of the literature that has challenged the central role of technology in business cycles.

A defining feature of the literature reviewed here lies in its search 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 industrialized 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 has been transformed using the bandpass filter developed in Baxter and King (1999), 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. As shown in King and Rebelo (1999), when the actual sequence of technology shocks (proxied by the estimated disturbances of an autoregres-



**Figure 1**  
Business-cycle fluctuations in output and hours

sive (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; the latter exercise can be viewed as a more stringent test of the RBC model than the usual moment-matching.

The literature reviewed in the present paper asks very different questions, however: What have been the effects of technology shocks in the postwar U.S. economy? 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 the tentative (and sometimes contradictory) answers that the efforts of a growing number of researchers have yielded. Some of that research has exploited the natural role of technological change as a source of permanent changes in labor productivity to identify technology shocks using structural vector autoregressions (VARs); other authors have instead relied on more direct measures of technological change and examined their comovements with a variety of macro variables. 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 little support for 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 dynamic stochastic general equilibrium (DSGE) model that incorporates both nominal and real frictions, and evaluates their respective roles. Section 7 concludes.

## 2. Estimating the Effects of Technology Shocks

In Galí (1999), the effects of technology shocks were identified and estimated using a structural VAR approach. In its simplest specification, to which we restrict our analysis here, the empirical model uses 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,  $x_t \equiv y_t - n_t$ . In what follows, the latter is assumed to be integrated of order one (in a way consistent with the evidence reported below). Fluctuations in labor productivity growth ( $\Delta x_t$ ) and in some stationary transformation of labor input ( $\hat{n}_t$ ) are assumed to be a consequence of two types of shocks hitting the economy and propagating their effects over time. Formally, the following moving average (MA) representation is assumed:

$$\begin{bmatrix} \Delta x_t \\ \hat{n}_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^d \end{bmatrix} \equiv C(L)\varepsilon_t \quad (1)$$

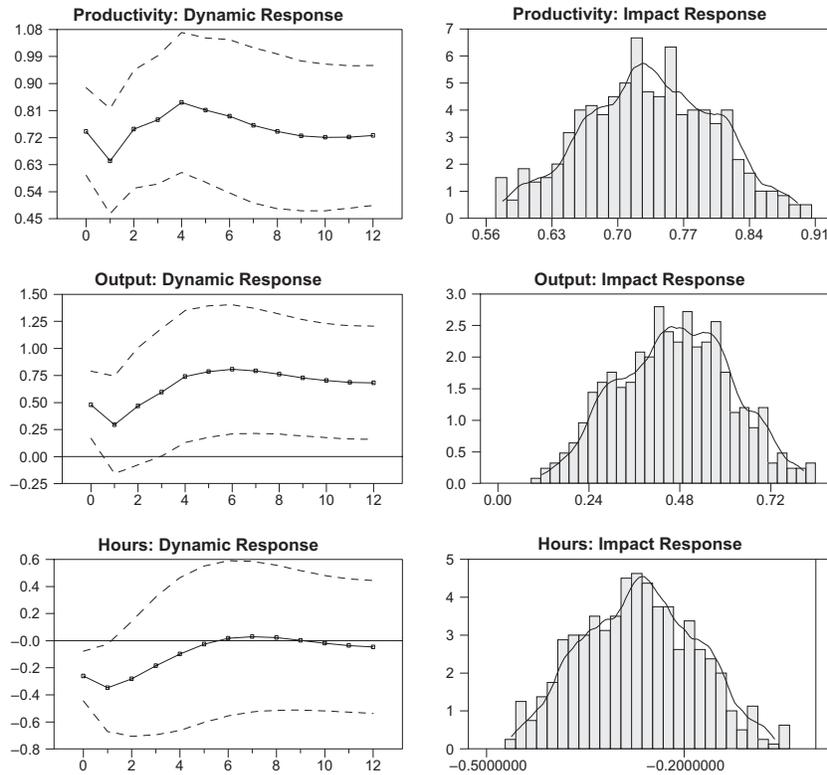
where  $\varepsilon_t^z$  and  $\varepsilon_t^d$  are serially uncorrelated, mutually orthogonal structural disturbances whose variance is normalized to unity. The polynomial  $|C(z)|$  is assumed to have all its roots outside the unit circle. Estimates of the distributed lag polynomials  $C^{ij}(L)$  are obtained by a suitable transformation of the estimated reduced form VAR for  $[\Delta x_t, \hat{n}_t]$  after imposing the long-run identifying restriction  $C^{12}(1) = 0$ .<sup>2</sup> That restriction effectively 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  $\{e_t^z\}$  as *technology shocks*. On the other hand, transitory shocks  $\{e_t^d\}$  can 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 have a permanent effect on output (but not on labor productivity), but which are nontechnological in nature, as would be the case for some permanent shocks to preferences or government purchases, among others.<sup>3</sup> 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). Below we often express the output and hours series in per-capita terms, using a measure of civilian noninstitutional population aged 16 and over (LNN).

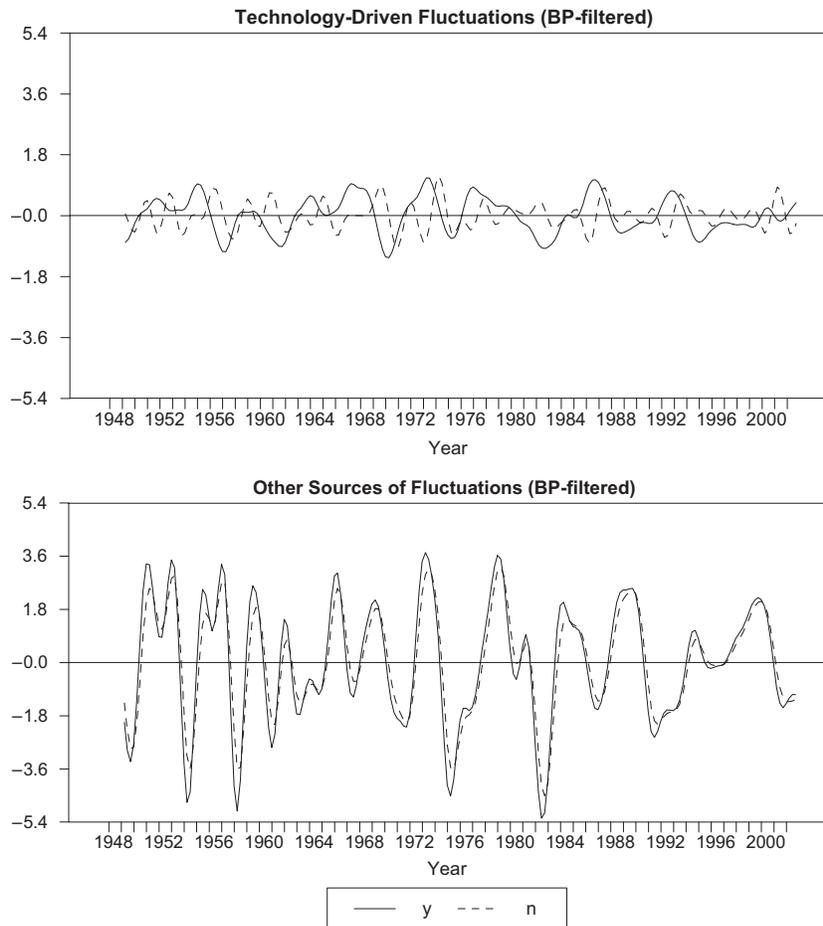
Our baseline estimates are based on a specification of hours in first-differences; i.e., we set  $\hat{n}_t = \Delta n_t$ . That choice seems consistent with the outcome of Augmented Dickey-Fuller (ADF) tests applied to the hours series, which do not reject the null of a unit root in the level of hours at a 10% significance level, against the alternative of stationarity around a linear deterministic trend. On the other hand, the null of a unit root in the first-differenced series is rejected at a level of less than 1%.<sup>4</sup> In a way consistent with the previous result, a Kwiatkowski et al. (1992) (KPSS) test applied to  $n_t$  rejects the stationarity null with a significance level below 1%, while failing to reject the same null when applied to  $\Delta n_t$ . In addition, the same battery of ADF and KPSS tests applied to our  $x_t$  and  $\Delta x_t$  series support the existence of a unit root in labor productivity, a necessary condition for the identification strategy based on long-run restrictions employed here. Both observations suggest the



**Figure 2**  
The estimated effects of technology shocks (*Difference specification, 1948:01–2002:04*)

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 a 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.<sup>5</sup> 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 technology shock that raises labor productivity permanently.<sup>6</sup> The point estimates suggest that hours do eventually return to their original level (or close to it), but not until more than a year later. Along with that pattern of hours, we observe a positive but muted initial response of output in the face of a positive technology shock.



**Figure 3**  
Sources of U.S. business cycle fluctuations (*Difference specification, sample period: 1948:01–2002:04*)

The estimated responses to a technology shock displayed in Figure 2 contrast starkly with the predictions 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.<sup>7</sup>

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 in Figure 3, which displays the estimated business-cycle components of the historical series for output and hours associated with technology and nontechnology

shocks. In both cases, the estimated components of the (log) levels of productivity and hours have been detrended using the same bandpass 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%, respectively. 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 to the conventional business-cycle fluctuations displayed in Figure 1.

The picture changes dramatically if we turn our attention to the estimated fluctuations of output and hours driven by shocks with no permanent effects on productivity (displayed in the bottom 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.

A possible criticism to the above empirical framework is the assumption of only two driving forces underlying the fluctuations in hours and labor productivity. As discussed in Blanchard and Quah (1989), ignoring some relevant shocks may lead to a significant distortion in the estimated impulse responses. Galí (1999) addresses that issue by estimating a five-variable VAR (including time series on real balances, interest rates, and inflation). That framework allows for as many as four shocks with no permanent effects on productivity, and for which no separate identification is attempted. The estimates generated by that higher-dimensional model regarding the effects of technology shocks are very similar to the ones reported above, suggesting that the focus on only two shocks may not be restrictive for the issue at hand.<sup>8</sup>

## 2.2 *Related Empirical Work*

The empirical connection between technological change and business-cycle fluctuations has been the focus of a rapidly expanding literature.

Next, we briefly discuss some recent papers that provide evidence on the effects of technology shocks, and that reach conclusions similar to Galí (1999), while using a different data set or empirical approach. We leave for later a discussion of the papers whose findings relate more specifically to the content of other sections, including those that question the evidence reported above.

An early contribution 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 sort out the component of productivity associated with exogenous technological change from the component that varies in response to other shocks that may affect the capital-labor ratio. 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 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 implies that such an effect lasts for about three quarters, after which unemployment starts to fall and returns rapidly to its original value.

As mentioned in Galí (1999, footnote 19) and stressed by Valerie Ramey in her comment about this paper (also in this volume), the finding of a decline in hours (or an increase in unemployment) in response to a positive technology shock could also have been detected by an attentive reader in a number of earlier VAR papers, though that finding generally goes unnoticed or is described as puzzling. Blanchard and Quah (1989) and Blanchard (1989) are exceptions because 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.”<sup>9</sup>

The work of Basu, Fernald, and Kimball (1999) deserves special attention here, given its focus and the similarity of its findings to those in Galí (1999) despite the use of an unrelated methodology. Basu, Fernald, and Kimball (BFK) use a sophisticated growth accounting methodology allowing for increasing returns, imperfect competition,

variable factor utilization, and sectoral compositional effects to uncover a time series for aggregate technological change in the postwar U.S. 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 its widely acknowledged 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 output showing no significant change (with point estimates suggesting 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 permanently higher plateau several years after the shock.

Kiley (1997) applies the structural VAR framework in Galí (1999) to data from two-digit manufacturing industries. While he does not report impulse responses, 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 attempts to identify 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, a sectoral labor input measure declines in response to a positive industry-specific technology shock. Using data from a large panel of 458 manufacturing industries and 35 sectors, Franco and Philippon (2004) estimate a structural VAR with three shocks: technology shocks (with permanent effects on industry productivity), composition shocks (with permanent effects on the industry share in total output), and transitory shocks. They find that technology shocks (1) generate a negative comovement between output and hours within each industry, and (2) are almost uncorrelated across industries. Thus, they conclude that technology shocks can account for only a small fraction of the variance of aggregate hours and output (with two-thirds of the latter accounted for by transitory shocks).

Shea (1998) uses a structural VAR approach to model the connection between changes in measures of technological innovation (research and development [R&D] and number of patent applications) and subsequent changes in total factor productivity (TFP) and hired inputs, us-

ing 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 but 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 a positive innovation in the technology indicator, inputs—including labor—are shown to respond in the direction opposite to the movement in TFP, a finding in line with the evidence above.<sup>10</sup>

Francis and Ramey (2003a) extend the analysis in Galí (1999) in several dimensions. The first modification they consider consists in augmenting the baseline VAR (specified in first differences) with a capital tax rate measure to sort out the effects of technology shocks from those of permanent changes in tax rates (more below). Second, they identify 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 Ramey show 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 asymptotic effect of that shock with one imposing a positive response of productivity at a horizon of ten years after the shock.

A number of recent papers have provided related evidence based on non-U.S. aggregate data. In Galí (1999), the structural VAR framework discussed above is also applied to the remaining G7 countries (Canada, the United Kingdom, France, Germany, Italy, and Japan). He uncovers a negative response of employment to a positive technology shock in all countries, with the exception of Japan. Galí (1999) also points out some differences in those estimates relative to those obtained for the United States: in particular, the (negative) employment response to a positive technology shocks in Germany, the United Kingdom, 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 European area as a whole can also be found in Galí (2004), which applies the same empirical framework to the quarterly data set that has recently been available. In particular, technology shocks are found to account for only 5% and 9% 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 evidence of a negative short-run impact of technology shocks on labor in every subsample.<sup>11</sup> Finally, Carlsson (2000) develops a variant of the empirical framework in BFK (1999) and Burnside et al. (1995) to construct a time series for technological change, and applies it to a sample of Swedish two-digit manufacturing industries. Most prominently, he finds that positive shocks to technology have, on impact, a contractionary effect on hours and a nonexpansionary effect on output, as in BFK (1999).

### 2.3 *Implications*

The implications of the evidence discussed above for business-cycle analysis and modeling 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 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 feature of the economy's response to aggregate technology shocks predicted by calibrated RBC models cannot be found in the data. Second, and to the extent that one takes the positive comovement between measures of output and labor input as a defining characteristic of the business cycle, it follows as a corollary that technology shocks cannot be a quantitatively important (and, even less, a dominant) source of observed aggregate fluctuations. While the latter implication is particularly damning for RBC theory, given its traditional emphasis on aggregate technology variations as a source of business cycles, its relevance is independent of one's preferred macroeconomic paradigm.

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

This section has two main objectives. First, we try to 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? We provide some evidence below 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 and that focus on the appropriate specification of hours (levels or first differences). Finally, we discuss a paper by Fisher (2003) that distinguishes between two types of technology shocks: neutral and investment-specific.

#### 3.1 *Are Long-Run Restrictions Useful in Identifying Technology Shocks?*

The approach to identification proposed in Galí (1999) relies on the assumption that only (permanent) technology shocks can have a permanent effect on (average) labor productivity. That assumption can be argued to hold under relatively weak conditions, satisfied by the bulk of business-cycle models currently used by macroeconomists. To review the basic argument, consider an economy whose technology can be described by an aggregate production function:<sup>12</sup>

$$Y_t = F(K_t, A_t N_t) \quad (2)$$

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:

$$\frac{Y_t}{N_t} = A_t F_k(k_t, 1) \quad (3)$$

where  $k_t \equiv K_t/(A_t N_t)$  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:

$$(1 - \tau)F_k(k, 1) = (1 + \mu) \left( \rho + \delta + \frac{\gamma}{\sigma} \right) \quad (4)$$

where  $\mu$  is the price markup,  $\tau$  is a tax on capital income,  $\rho$  is the time discount rate,  $\delta$  is the depreciation rate,  $\sigma$  is the intertemporal elasticity of substitution, and  $\gamma$  is the average growth rate of (per-capita) consumption and output. Under the assumption of decreasing returns to capital, it follows from equation (4) that the capital labor ratio  $k$  will be stationary (and will thus fluctuate around a constant mean) as long as all the previous parameters are constant (or stationary). In that case, equation (3) 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  $\rho$ ,  $\delta$ ,  $\sigma$ , and  $\gamma$  are generally assumed to be constant in most examples and applications found in the business-cycle literature. The price markup  $\mu$  is more likely to vary over time, possibly 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) are non-stationary, the latter would more likely 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.<sup>13</sup> Finally, notice that the previous approach to identification of technology shocks requires that (1)  $F_k$  be decreasing, so that  $k$  is uniquely pinned down by equation (4), and (2) 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.<sup>14</sup>

### 3.1.1 Do Capital Income Tax Shocks Explain Permanent Changes in Labor Productivity?

The previous argument is much less appealing, however, when applied to the capital income tax rate. As Uhlig (2004) and others have pointed out, the assumption of a stationary capital income tax rate may be unwarranted, given the behavior of measures for that variable over the postwar period. This is illustrated in Figure 4, which displays two alternative measures of the capital income tax rate in the United States. 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 that corresponds to an updated version of the one used in McGrattan (1994).<sup>15</sup> Henceforth we denote those series by  $\tau_t^J$  and  $\tau_t^M$ , respectively. Both series display an apparent nonstationary 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.

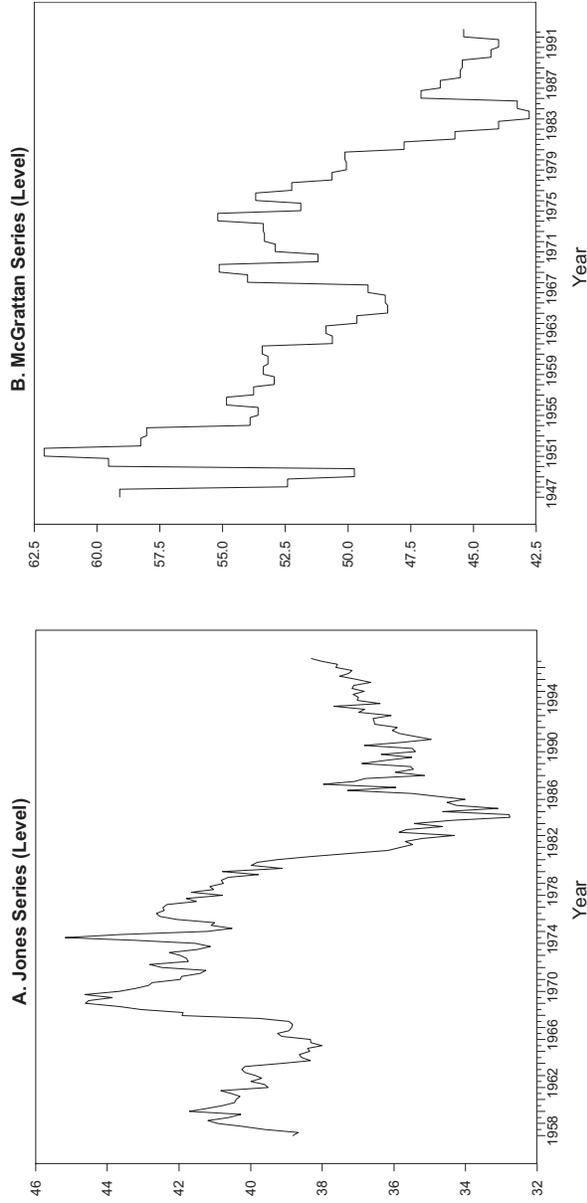
As shown in Figures 4.C and 4.D, which display the same series in first differences, the presence of sizable short-run variations in those measures of capital taxes could hardly be captured by means of some deterministic or smooth function of time (their standard deviations being 0.79% for the quarterly 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 by augmenting the VAR with a capital tax rate variable, in addition to labor productivity and hours. As mentioned above, 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.

Here, we revisit the hypothesis of a tax rate shock mistaken for a technology shock by looking for evidence of some comovement between (1) the permanent shock  $\varepsilon_t^z$  estimated using the structural VAR discussed in Section 2, and (2) 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 series as (alternative) proxies for the shocks to the capital income tax rate. 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



**Figure 4**  
Capital income tax rates

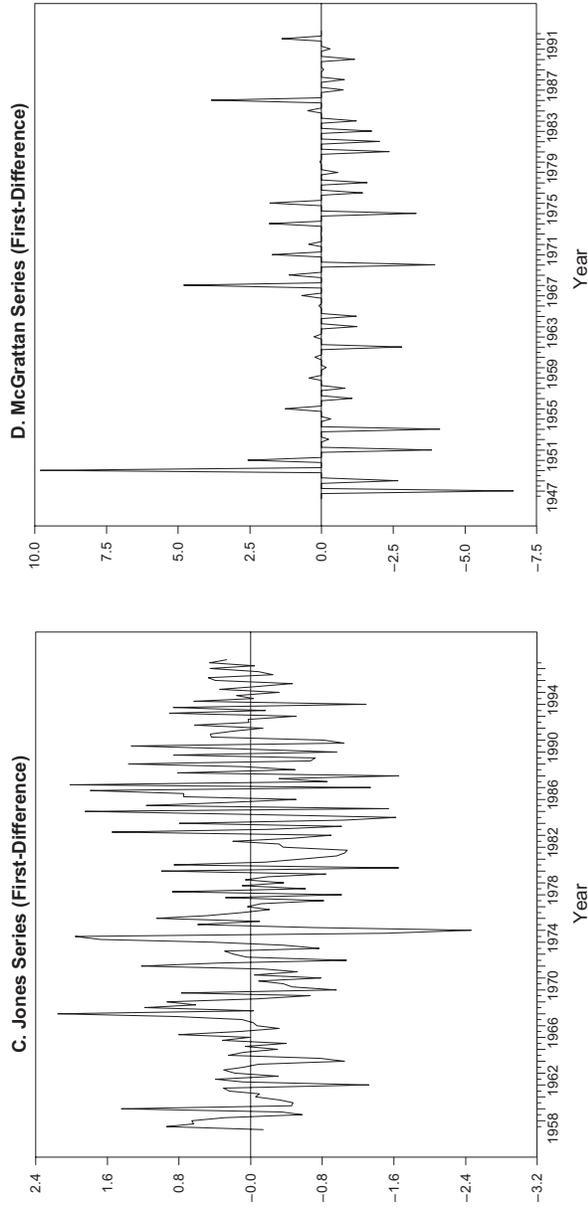


Figure 4  
(continued)

the permanent shocks from the VAR. More precisely, our estimates of  $\text{corr}(\Delta\tau_t^J, \varepsilon_t^z)$  and  $\text{corr}(\Delta\tau_t^M, \varepsilon_t^z)$  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.

Second, an ordinary least squares (OLS) regression of the Jones tax series  $\Delta\tau_t^J$  on current and lagged values of  $\varepsilon_t^z$  yields jointly insignificant coefficient estimates: the  $p$ -value 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  $\varepsilon_t^z$ , with the  $p$ -value 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 a possible 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.<sup>16</sup>

### 3.1.2 Do Permanent Shocks to Labor Productivity Capture Variations in Technology?

Having all but ruled out variations in capital taxes as a significant factor behind the unit root in labor productivity, we present next some evidence that favors the interpretation of the VAR permanent shock as a shift to aggregate technology. 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 among several indicators that are viewed as independent of technology on one hand, and the VAR-based technology shock on the other. The indicators include the Romer and Romer (1989) monetary shock dummy, the Hoover and Perez (1994) oil shock dummies, Ramey and Shapiro's (1998) military buildup dates, and the federal funds rate. Francis and Ramey show that none of them

have a significant predictive power for the estimated technology shock.

Here, we provide a more direct assessment by using the measure of aggregate technological change obtained by Basu, Fernald, and Kimball (1999).<sup>17</sup> 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 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% 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).

Second, the correlation between our estimated VAR transitory shock and the BFK series is slightly negative, though insignificantly different from zero (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.

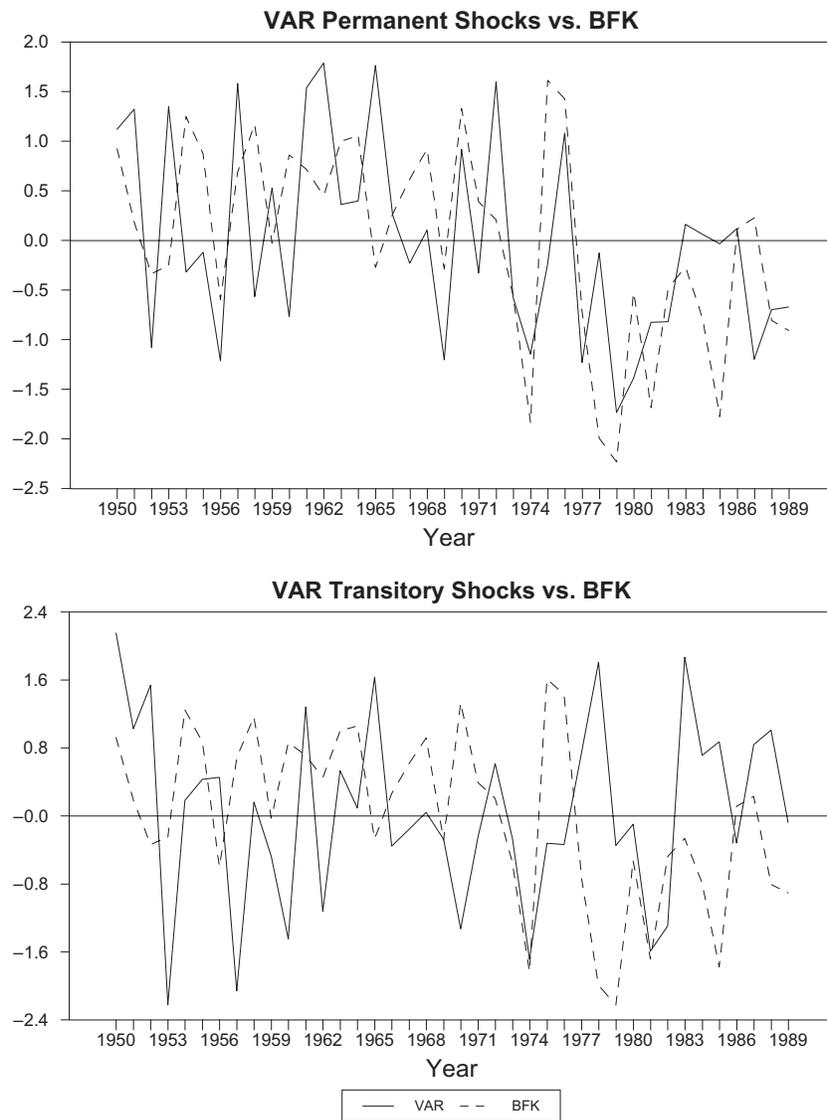
Finally, and given that the BFK series is mildly serially correlated, we have also run a simple OLS regression of the (normalized) BFK variable on its own lag, and the contemporaneous estimates of the permanent and transitory shocks from the VAR. The estimated equation, with  $t$  statistics in brackets,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

$$BFK_t = 0.29 BFK_{t-1} + 0.67 \varepsilon_t^z - 0.32 \varepsilon_t^d$$

$$(1.85) \quad (2.16) \quad (-1.11)$$

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



**Figure 5**  
Technology shocks: VAR versus BFK

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.

### 3.2 *Robustness to Alternative VAR Specifications*

Christiano, Eichenbaum, and Vigfusson (2003) have questioned some of the VAR-based evidence regarding the effects of technology shocks found in Galí (1999) and Francis and Ramey (2003a), on the basis of their lack of robustness to the transformation of labor input used. In particular, Christiano, Eichenbaum, and Vigfusson (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 ( $\hat{n}_t = n_t$ )—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, i.e., a negative comovement between output (or productivity) and hours in response to technology shocks. Perhaps most interesting, 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 vice versa. 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.<sup>18</sup> 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, the point estimate of the impact response of hours worked to a positive technology is now positive, though very small. 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 is sufficient, however, to generate a positive correlation (0.88) between output and hours conditional on the technology shock. As 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

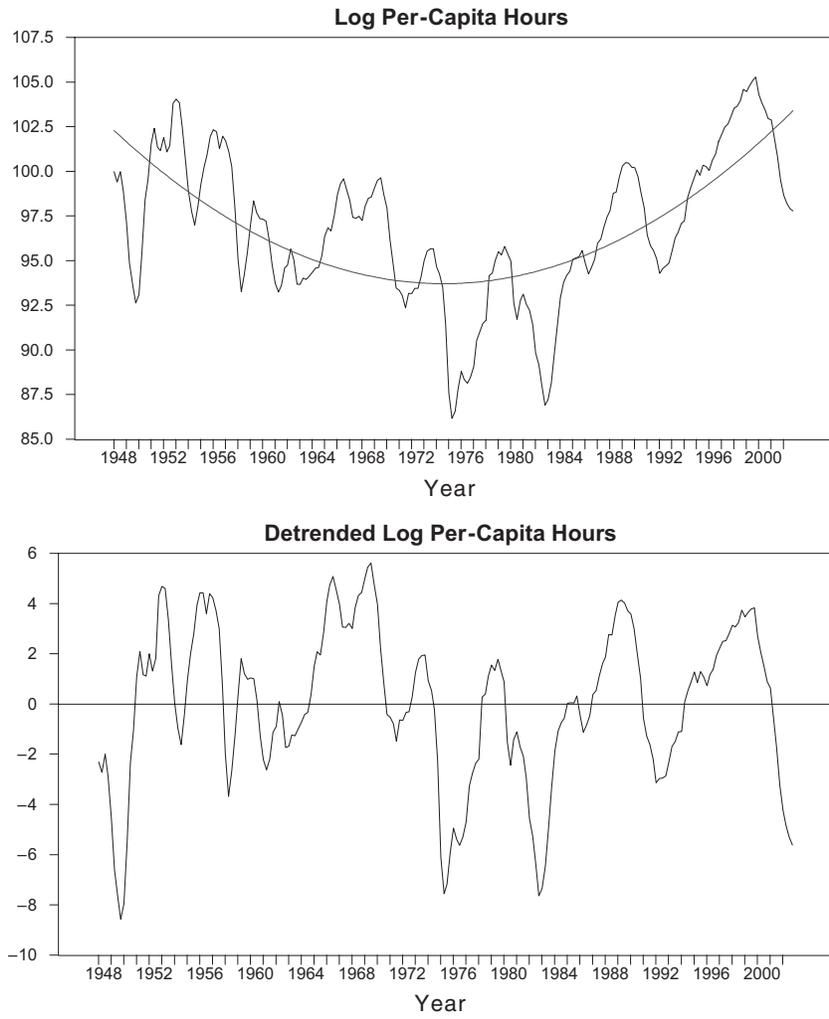
**Table 1**

The effects of technology shocks on output and hours in the nonfarm business sector

	Contribution to		Conditional	Impact on $n$ and $y$	
	$\text{var}(y)$	$\text{var}(n)$	$\text{corr}(y, n)$	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

hours at business-cycle frequencies (37 and 11%, respectively), though that fraction is larger than the one implied by the difference specification estimates.<sup>19</sup>

While we find the encompassing approach adopted by CEV enlightening, their strategy of 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 United States over the postwar period, displayed in Figure 6, is not 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. 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% significance level in both cases.<sup>20</sup> Figure 6 displays the fitted quadratic trend and the associated residual, 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



**Figure 6**  
Hours worked, 1948–2002

response to a positive technology shock, and a slightly 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%, essentially the same as under difference specification; see Table 1).<sup>21</sup>

To assess further the robustness of the above results, we have also conducted the same 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 independent of whether labor input is measured in per-capita terms since labor productivity is invariant to that normalization.<sup>22</sup> The second panel in Table 1 summarizes the results corresponding to three alternative transformations considered (first differences, levels, quadratic detrending). 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. 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.<sup>23</sup> 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% of the variance of hours, obtained under the level and detrended specifications.

As an additional check on the robustness of our findings, we have also 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: independent of the transformation of employment used, our estimates point to a decline in that variable in the short run in response to a positive technology shock, as well as a very limited contribution of technology shocks to the variance of GDP and employment. We should stress that we obtained those findings 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, we uncover a decline in labor input

**Table 2**  
The effects of technology shocks on GDP and employment

	Contribution to		Conditional	Impact on $n$ and $y$	
	$\text{var}(y)$	$\text{var}(n)$	$\text{corr}(y, n)$	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

in response to a positive technology shock, in a way consistent with the literature reviewed in Section 2. 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%. 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.

Fernald (2004) makes an important contribution to the debate by uncovering the most likely source of the discrepancy of the estimates when hours are introduced in levels. In particular, he shows the existence of a low-frequency correlation between labor productivity growth and per-capita hours. As illustrated through a number of simulations, the presence of such a correlation, while unrelated to the higher-frequency phenomena of interest, can distort significantly the estimated short-run responses. Fernald illustrates that point most forcefully by re-estimating the structural VAR in its levels specification (as in CEV), though allowing for two (statistically significant) trend breaks in labor productivity (in 1973:I and 1997:II): the implied impulse responses point to a significant decline in hours in response to a technology shock, a result that also obtains when the difference specification is used.

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 U.S. data point to considerable sensitivity of the estimates across subsample periods and the choice of transformation for hours. To assess the validity of the different specifications, they look at their implications for the persistence of the productivity response to a nontechnology 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 between hours and output in response to a shock that has a permanent effect on technology in the postwar period. In the pre-World War II 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 U.K. data (and a difference specification), they find a clear negative comovement of employment and output both in the pre-World War II and postwar sample periods.<sup>24</sup>

In light of those results and the findings in the literature discussed above, we conclude that 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 assessment is affected once we allow for technology shocks that are investment-specific.

### 3.3 *Investment-Specific Technology Shocks*

In a series of papers, Greenwood, Hercowitz, and Huffman (1988), and Greenwood, Hercowitz, and Krusell (1997, 2000) put forward and analyze 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 shock in eliciting a change in the quantity of input services hired by firms. Greenwood, Hercowitz, and Krusell (GHK) 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 are the only driving force. They conclude that the latter can account for about 30% of U.S. 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.

Fisher (2003) revisits the evidence on the effects of technology shocks and their role in the U.S. business cycle and uses an empirical framework that allows for separately identified sector-neutral and investment-specific technology shocks (which, following Fisher, we refer to, respectively, as N-shocks and I-shocks). In a way consistent with the identification scheme proposed in Galí (1999), both types of technology shocks are allowed to have a permanent effect on labor productivity (in contrast with nontechnology shocks). In a way consistent with the GHK framework, only investment-specific technology shocks are allowed to affect permanently the relative price of new investment goods. Using times series for labor productivity, per-capita hours, and the price of equipment (as a ratio to the consumption goods deflator) constructed by Cummins and Violante (2002), Fisher estimates impulse responses to the two types of shocks and their relative contribution to business-cycle fluctuations. We have conducted a similar exercise and have summarized some of the findings in Table 3.<sup>25</sup> 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 labor input measures 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 between those two variables.

The results for I-shocks are different in at least two respects. First, and as stressed in Fisher (2003), I-shocks generate a high positive

**Table 3**  
Investment-specific technology shocks: the Fisher model

	Contribution of N-shocks to:			Contribution of I-shocks 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

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 differences or are quadratically detrended, the contribution becomes much smaller and always remains below one-fourth.

What do we conclude from this exercise? First of all, the evidence does not speak with a single voice: whether technology shocks are given a prominent role or not as a source of business cycles depends on the transformation of the labor input measure used in the analysis.

Perhaps more interesting, 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. Explaining the Effects of Technology Shocks

In this section, we briefly discuss some of the economic explanations for the anomalous response of labor input measures to technology shocks. As a matter of simple accounting, firms' use of inputs (and labor, in particular) will decline in response to a positive technology shock only if they choose (at least on average) to adjust their level of output less than proportionally to the increase in total factor productivity. Roughly speaking, we can think of two broad classes of factors that are absent in the standard RBC model and that could potentially generate that result. The first class involves the presence of nominal frictions, combined with certain monetary policies. The second set of explanations is unrelated to the existence of nominal frictions, so we refer to it as real explanations. We discuss them in turn next.

##### 4.1 *The Role of Nominal Frictions*

A possible explanation for the negative response of labor to a technology shock, 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, 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.<sup>26</sup> 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 a stylized model economy in which the relationship  $y_t = m_t - p_t$  holds in equilibrium,<sup>27</sup> firms set prices in advance (implying a predetermined price level), and the central bank follows a simple money-supply rule. It is easy to see that, in that context, employment will experience a short-run decline in response to positive technology shocks, unless the central bank endogenously expands the money supply (at least) in proportion to the increase in productivity. 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 downward 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 (e.g., Dotsey, 2002). 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.

#### 4.1.1 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 à 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:

$$y_t = E_t\{y_{t+1}\} - \sigma(r_t - E_t\{\pi_{t+1}\}) \quad (5)$$

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  $\sigma$  can be broadly interpreted as 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:

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \kappa(y_t - \bar{y}_t) \quad (6)$$

where  $\bar{y}_t$  is the natural level of output (or potential output), defined as the one that would prevail in the absence of nominal frictions. The variable  $\bar{y}_t$  can also 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 (1983). In that context, coefficient  $\kappa$  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.

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:<sup>28</sup>

$$\bar{y}_t = \bar{\psi}_y a_t \quad (7)$$

where  $a_t$  represents an exogenous technology parameter. The latter is assumed to follow 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  $\bar{n}_t$ :

$$\bar{n}_t = \bar{\psi}_n a_t$$

where  $\bar{\psi}_n \equiv (\bar{\psi}_y - 1)/(1 - \alpha)$ . 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  $\bar{\psi}_y \geq 1$  (and hence  $\bar{\psi}_n > 0$ ). 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. It is precisely this property that makes it possible for any technology-driven RBC model to generate equilibrium fluctuations that replicate some key features of observed business cycles, including a positive comovement of output and employment.<sup>29</sup>

In that context, a natural question is, To what extent is the comovement of output and employment in response to technology shocks found in the evidence described above the result of the way monetary policy has been conducted in the United States and other industrialized economies? To illustrate that point, we use the simple model above and derive the implications for the effects of technology shocks of having the central bank follow an interest rate rule of the form:

$$r_t = \phi_\pi \pi_t + \phi_y y_t \quad (8)$$

A rule similar to equation (8) has been proposed by Taylor (1993) and others as a good characterization of monetary policy in the United States 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.<sup>30</sup>

Combining equation (8) with equilibrium conditions in equations (5) and (6), we can derive the following closed-form expression for equilibrium output:

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

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  $\Theta$  is greater than 0 guarantees that a positive (negative) technology shock raises (lowers) output, as in the standard RBC model. On the other hand,  $\Theta \leq 1$  implies that:

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

i.e., in the presence of nominal frictions, the size of response of output to a technology shock,  $\psi_y$ , is bounded above by that implied by the corresponding RBC model ( $\bar{\psi}_y$ ) when the central bank follows the rule in equation (8). Hence, the combination of sticky prices and a Taylor rule will tend to overstabilize the output fluctuation resulting from technology shocks. We can interpret parameter  $\Theta$  as an index of *effective policy accommodation*, i.e., one that measures the extent to which the Taylor rule in equation (8) accommodates the changes in potential output resulting from variations in technology shocks, given the persistence of the latter and the rest of the parameters describing the economy. Notice that the index of effective policy accommodation  $\Theta$  is increasing in the size of the inflation coefficient in the Taylor rule ( $\phi_\pi$ ), and in the effectiveness of interest changes (as reflected by  $\sigma$ ). It is also positively related to  $\kappa$  (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 ( $\phi_y$ ).

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

$$n_t = \left( \frac{\Theta \bar{\psi}_y - 1}{1 - \alpha} \right) a_t$$

$$\equiv \psi_n a_t$$

Notice that, in a way analogous to the output case, we have  $\psi_n \leq \bar{\psi}_n$ . 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. It is clear that the impact of a technology shock on employment may be positive or negative, depending on the configuration of parameter values.

We can get a sense for the likely sign and plausible magnitude for  $\psi_n$  by using conventional values used in calibration exercises in the literature involving similar models. Thus, Rotemberg and Woodford's (1999) estimates, based on the response to monetary policy shocks, imply a value of 0.024 for  $\kappa$ . A unit value is often used as an upper bound for  $\sigma$ . Taylor's widely used values for  $\phi_\pi$  and  $\phi_y$  are 1.5 and 0.5, respectively. 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 controversial. Under those assumptions, we obtain a value for  $\Theta$  of 0.28. The latter figure points to a relatively low degree of effective policy accommodation.

Using a standard calibrated RBC model, Campbell (1994) obtains a range of values for  $\bar{\psi}_y$  between 1 and 2.7, depending on the persistence of the shock and the elasticity of the labor supply. In particular, given a unit labor supply elasticity and a 0.95 autocorrelation in the technology process, he obtains an elasticity  $\bar{\psi}_y$  of 1.45, which we adopt as our benchmark value.<sup>31</sup> When we combine the latter with our calibrated value for  $\Theta$  computed, we obtain an implied benchmark elasticity of employment  $\psi_n$  equal to  $-0.87$ .

The previous calibration exercise, while admittedly quick and loose, illustrates that condition  $\psi_n < 0$  is likely to hold under a broad range of reasonable parameter values. 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.<sup>32</sup>

In his seminal paper, Prescott (1986b) 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!

#### 4.1.2 Nominal Rigidities and the Effects of Investment-Specific Technology Shocks

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 discussed in Section 3 above. The argument can be made most clearly in the context of a sticky-price version of a model like that in the GHK (2000) model. Once again, let us say 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, 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 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.

#### 4.1.3 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. Next, we briefly describe a sample of those papers.

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) 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 policy 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 responses to a technology shock. In particular, they show that the decline in hours in response to a positive technology shock is much more pronounced in the pre-Volcker period and is 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 and not so much on the stabilization of economic activity.<sup>33</sup>

Some evidence at the micro-level is provided by Marchetti and Nucci (2004), who exploit 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 construct a time series for total factor productivity at the firm level,

and estimate the responses of a number of firm-specific variables to an innovation in the corresponding technology measure. Among other findings, they provide evidence of a negative impact effect of a technology shock on labor input. Most interesting is that 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.<sup>34</sup>

#### 4.2 *Real Explanations*

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.<sup>35</sup> 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 be-

tween 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. 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 in the 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 (2003) 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 the 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 unrelated to the cyclical variations associated with a detrended measure 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 to 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 responses are so smooth, they imply very small movements at cyclical frequencies. It follows that technology shocks with such characteristics will account only for a small fraction of observed cyclical fluctuations in output and hours.

Collard and Dellas (2002) emphasize an additional mechanism, specific to an open economy, through which technology shocks may induce short-run negative comovements between output and labor input even in the absence of nominal rigidities. They analyze a 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 deterioration in its terms of trade (i.e., a large decline in 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 nonnegligible 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 that 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 structural VAR and the underlying structural parameters that determine the degree of those frictions. As a result, 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 either nominal or real frictions were 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.

## **5. Technology Shocks and the Business Cycle in an Estimated DSGE Model**

In this section, we try to sort out the merits of the two types of explanations discussed above by estimating and analyzing a framework that incorporates both types of frictions and that is sufficiently rich to be taken to the data. The features that we incorporate include habit formation in consumption, staggered price- and wage-setting à 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. 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 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 recent years, in a variety of contexts.<sup>36</sup> 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 European area and the United States. Lubik and Schorfheide (2003b) use the Bayesian framework to estimate a small-scale model allowing for indeterminacy. Rabanal (2003) estimates a general equilibrium model for the United States and the European area in search for cost channel effects of monetary policy.<sup>37</sup>

Next we summarize the set of equilibrium conditions of the model.<sup>38</sup> The demand side of the model is represented by the Euler-like equation:

$$b\Delta y_t = E_t\{\Delta y_{t+1}\} - (1-b)(r_t - E_t\{\pi_{t+1}\}) + (1-\rho_g)(1-b)g_t \quad (9)$$

which modifies equation (5) above by allowing for some external habit formation (indexed by parameter  $b$ ) and introducing a preference shock  $\{g_t\}$  that follows an AR(1) process with coefficient  $\rho_g$ . Underlying equation (9) is an assumption that preferences are separable between consumption and hours, and logarithmic in the quasidifference of consumption to preserve the balanced growth path property.<sup>39</sup> Aggregate output and hours are related by the simple log-linear production function:

$$y_t = a_t + n_t$$

Using a tilde to denote variables normalized by current productivity (to induce lack of movement), we have:

$$\tilde{y}_t = n_t \quad (10)$$

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 average (log) markup from its steady-state level, which we denote by  $\mu_t^p$ :<sup>40</sup>

$$\pi_t = \gamma_b \pi_{t-1} + \gamma_f E_t\{\pi_{t+1}\} - \kappa_p (\mu_t^p - u_t) \quad (11)$$

where  $\gamma_b = \eta_p/(1 + \beta\eta_p)$ ,  $\gamma_f = \beta/(1 + \beta\eta_p)$ ,  $\kappa_p = (1 - \beta\theta_p)(1 - \theta_p)/\theta_p(1 + \eta_p\beta)$ ,  $\theta_p$  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  $\mu_t^p = -\log(W_t/P_tA_t) \equiv -\tilde{\omega}_t$  is the price markup, where  $\tilde{\omega}_t = \omega_t - a_t$  is the real wage per efficiency unit. Variable  $u_t$  denotes exogenous variations in the desired price markup.

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

$$\begin{aligned} \tilde{\omega}_t = & \frac{1}{1 + \beta} \tilde{\omega}_{t-1} + \frac{\beta}{1 + \beta} E_t\{\tilde{\omega}_{t+1}\} - \frac{1}{1 + \beta} \Delta a_t + \frac{\beta}{1 + \beta} E_t\{\Delta a_{t+1}\} \\ & + \frac{\eta_w}{1 + \beta} \pi_{t-1} - \frac{(1 + \beta\eta_w)}{1 + \beta} \pi_t + \frac{\beta}{1 + \beta} E_t\{\pi_{t+1}\} - \frac{\kappa_w}{1 + \beta} (\mu_t^w - v_t) \end{aligned} \quad (12)$$

where  $\theta_w$  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  $\kappa_w \equiv (1 - \theta_w)(1 - \beta\theta_w)/\theta_w(1 + \varepsilon_w\varphi)$ , and  $\varepsilon_w$  is the wage elasticity of labor demand in the steady state. Also notice that  $\mu_t^w \equiv \tilde{\omega}_t - ((1/(1 - b))\tilde{y}_t - (b/(1 - b))\tilde{y}_{t-1} - g_t + (b/(1 - b))\Delta a_t + \varphi n_t)$  is the wage markup. Variable  $v_t$  denotes exogenous variations in the desired wage markup.

Finally, we close the model by assuming that the monetary authority adjusts interest rates in response to changes in inflation and output growth according to the rule:

$$r_t = \phi_r r_{t-1} + (1 - \phi_r)\phi_\pi \pi_t + (1 - \phi_r)\phi_y \Delta y_t + z_t \quad (13)$$

where  $z_t$  is an exogenous monetary shock.<sup>41</sup>

The exogenous driving variables are assumed to evolve as follows:

$$a_t = a_{t-1} + \varepsilon_t^a$$

$$g_t = \rho_g g_{t-1} + \varepsilon_t^g$$

$$u_t = \rho_u u_{t-1} + \varepsilon_t^u$$

$$v_t = \rho_v v_{t-1} + \varepsilon_t^v$$

$$z_t = \varepsilon_t^z$$

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.

## 5.1 Parameter Estimation

### 5.1.1 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 1948:1 to 2002:4. For consistency 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. To render the series 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 known from Bayes's 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.<sup>42</sup> 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 the posterior distribution of the parameters.

### 5.1.2 The Likelihood Function

Let  $\psi$  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  $\varepsilon_t$  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:

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

$$z_t = N(\psi)z_{t-1} + \varepsilon_t$$

$$E(\varepsilon_t \varepsilon_t') = \Sigma(\psi)$$

We use standard solution methods for linear models with rational expectations (see, for example, 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  $L(\{x_t\}_{t=1}^T | \psi)$  the likelihood function of  $\{x_t\}_{t=1}^T$ .

### 5.1.3 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 the first three columns of 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 prior for all these parameters has support between 0 and 1, except the probabilities of the Calvo lottery, which 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.

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 guarantee nonnegativity). We select their hyperparameters to match available information for the prior mean standard deviation of the innovations, while allowing reasonable uncertainty in these parameters. For instance, for the monetary policy rule, we choose the means of the inflation and output growth coefficients to match the ones proposed by Taylor.<sup>43</sup> For the monetary policy shock, we use the standard deviation that comes from running an OLS regression for the Taylor rule equation.

In addition, we fix some parameters. We set the discount factor at  $\beta = 0.99$ . The elasticities of product and labor demand are set to 6 (implying steady-state markups of 20%). These values are pretty conventional in the literature.

**Table 4**  
Prior and posterior distributions

Parameter	Prior distribution		Posterior distribution		
		Mean	Standard deviation	Mean	Standard deviation
$b$	Uniform(0, 1)	0.50	0.289	0.42	0.04
$\varphi$	Normal(1, 0.25)	1.00	0.25	0.80	0.11
$\theta_p$	Uniform(0, 0.9)	0.45	0.259	0.53	0.03
$\theta_w$	Uniform(0, 0.9)	0.45	0.259	0.05	0.02
$\eta_p$	Uniform(0, 1)	0.50	0.289	0.02	0.02
$\eta_w$	Uniform(0, 1)	0.50	0.289	0.42	0.28
$\rho_r$	Uniform(0, 0.97)	0.485	0.284	0.69	0.04
$\phi_y$	Normal(0.5, 0.125)	0.50	0.13	0.26	0.06
$\phi_\pi$	Normal(1.5, 0.25)	1.50	0.25	1.35	0.13
$\rho_g$	Uniform(0, 0.97)	0.485	0.284	0.93	0.02
$\rho_u$	Uniform(0, 0.97)	0.485	0.284	0.95	0.02
$\rho_v$	Uniform(0, 0.97)	0.485	0.284	0.91	0.01
$\sigma_z$	Gamma(25, 0.0001)	0.0025	0.0005	0.003	0.000
$\sigma_a$	Gamma(25, 0.0004)	0.01	0.002	0.009	0.001
$\sigma_g$	Gamma(16, 0.00125)	0.02	0.005	0.025	0.0024
$\sigma_u$	Gamma(4, 0.0025)	0.01	0.005	0.011	0.001
$\sigma_v$	Gamma(4, 0.0025)	0.01	0.005	0.012	0.001

#### 5.1.4 Drawing from the Posterior

From Bayes's 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  $\psi$ . 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 (2003a) and use the random walk Metropolis-Hastings algorithm to obtain a random draw of size 500,000 from  $p(\psi | \{x_t\}_{t=1}^T, m)$ . We use the draw to estimate the moments of the posterior distribution and to obtain impulse responses and second moments of the endogenous variables.

## 5.2 *Main Findings*

### 5.2.1 **Parameter Estimates and Second Moments**

The last two columns of Table 4 report the mean and standard deviation of the posterior distributions for all the parameters. Notice that 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). The parameter that measures the elasticity of the marginal disutility of hours,  $\varphi$ , is estimated to be 0.80, which is close to values usually obtained or calibrated in the literature.

The average duration of price contracts implied by the point estimate of the price stickiness parameter lies slightly above two quarters. We view this estimate as a moderate amount of price stickiness in the economy. Perhaps most surprising is the low degree of wage stickiness uncovered by our estimation method. Such an implausible low estimate may suggest that the Calvo model is not the best formalism to characterize wage dynamics.<sup>44</sup>

The price indexation coefficient is estimated at a low value, 0.04, suggesting that the pure forward-looking model is a good approximation for inflation dynamics, once we allow for autoregressive price markup 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. The estimated processes for the shocks of the model suggest that all of them are highly autocorrelated, with parameters between 0.95 for the price markup shock and 0.91 for the wage markup shock.<sup>45</sup>

Table 5 displays some selected posterior second moments implied by the model estimates and compares them to the data.<sup>46</sup> The first two columns present the standard deviation of the observed variables, and their counterparts implied by the estimated 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 well in mimicking the unconditional correlation between the growth rates of hours and output: in the data, it is 0.75; in the model, it is 0.72. However, it overestimates the standard deviation of hours (3.11% in

**Table 5**  
Second moments of estimated DSGE model

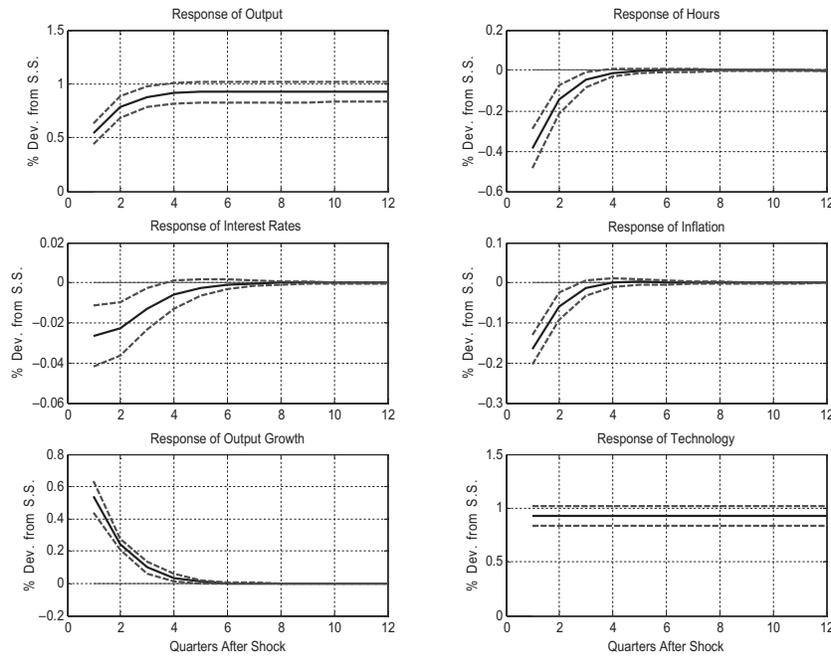
	Standard deviations (%)		Contribution to variance	
	Data	Model	Technology component	Technology shocks
Original data				
Output growth	1.36	1.27	0.60	22.3%
Inflation	0.72	0.73	0.18	6.0%
Interest rate	0.72	0.67	0.04	0.3%
Hours	3.11	4.60	0.42	0.8%
Real wage/output	3.69	4.44	0.13	0.1%
Correlation between ( $dy, dn$ )	0.75	0.72	-0.49	
Bandpass filtered data				
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	

the data and 4.6% in the model) and to a lesser extent the real wage–output ratio (3.69% in the data, 4.44% in the model).

### 5.2.2 The Effects of Technology Shocks

Next, we turn our attention to the estimated model's predictions regarding the effects of technology shocks.<sup>47</sup> Figure 7 displays the posterior impulse responses to a permanent technology shock of a size normalized to one standard deviation.<sup>48</sup> 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 persistent decline in hours in response to a positive technology shock, and a gradual adjustment of output to a permanently higher plateau. It takes about four quarters for output to reach its new steady-state level. Hours drop on impact, by about 0.4 percentage points, and converge monotonically to their initial level afterward.<sup>49</sup>

The third column of Table 5 reports the second moments of the observed variables conditional 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.<sup>50</sup> We can see that technology shocks do not play a major role in explaining the variability of the five observed variables. They explain 22% of the variability of output growth and 6% of the variability of inflation. For the rest of

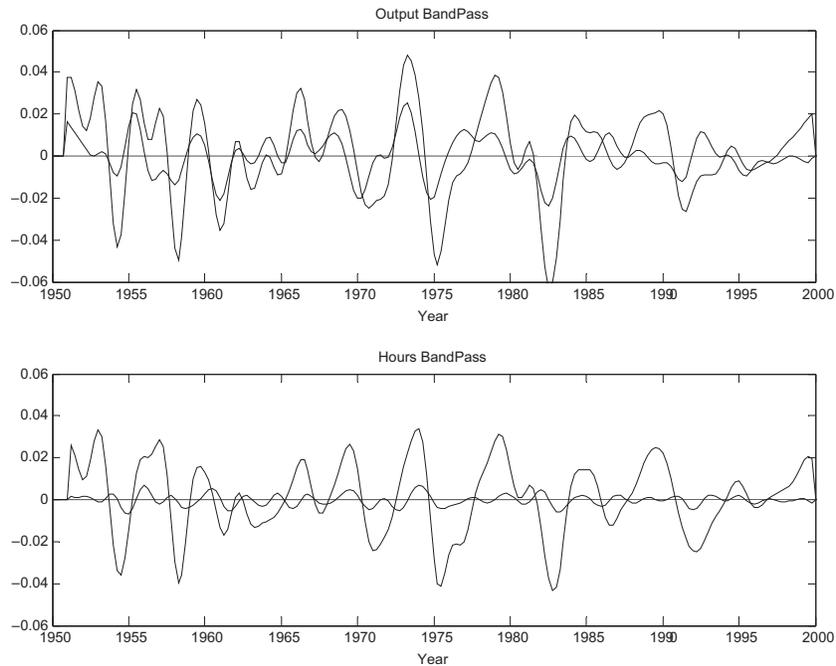


**Figure 7**  
Posterior impulse responses to a technology shock: model based estimates

variables, including hours, they explain an insignificant amount of overall volatility. 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 5 report statistics based on bandpass filtered data. In this case, the series of output growth and hours generated by the estimated model (when all shocks other than technology are turned off) are used to obtain the (log) levels of hours and output, on which the bandpass filter is applied. Once again, we find that technology shocks can account for only a small fraction 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 findings are illustrated in Figure 8, which displays the business-cycle components of log output and log hours associated with technology shocks, according to our estimated model. It is apparent



**Figure 8**

The role of technology shocks in U.S. postwar fluctuations: model-based estimates

Note: Solid line: technology component (BP-filtered); dashed line: U.S. data (BP-filtered).

that technology shocks explain only a minor fraction of output 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 (2004), and Smets and Wouters (2003b), using slightly different models and/or estimation methods.

### 5.2.3 What Are the Main Sources of Economic Fluctuations?

Which shocks play a more important role in explaining fluctuations in our observed variables? In Table 6, we report the contribution of each shock to the total variance of each variable implied by our model estimates. The shock that explains most of the variance of all variables in our framework is the preference shock, which we can interpret more broadly as a (real) demand shock. It explains above 70% of the variance of hours, the real wage-output ratio, and the nominal interest rate. The preference shock also explains 57% of the variance of output

**Table 6**  
Variance decomposition from estimated DSGE model

	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%

and 36% of the variance of inflation. On the other hand, the monetary shock explains only approximately 5% of output growth and the nominal interest rate, and is an important determinant of inflation variability, contributing to 27% of total volatility. Price and wage markup shocks both have some importance in explaining the volatility of all variables, with contributions to the variance that range from 7% to 17%. Overall, the picture that emerges from Table 6 is that preference shocks are key for explaining the volatility of all variables. The monetary and technology shocks have some importance in the sense that they explain about 20% 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.

#### 5.2.4 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 7, we present the correlation between the business-cycle components of output and hours 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, and habit formation. When we shut down each of those, we find that the remaining rigidities still induce a large and negative

**Table 7**

Technology-driven fluctuations output and hours: correlations implied by alternative model specifications (BP-filtered data)

Original	-0.14
Flexible wages	-0.16
Flexible prices	-0.18
No habit formation	-0.29
Flexible prices and wages	-0.21
No frictions (RBC)	0.22
Inflation targeting	-0.15

conditional correlation. For instance, in the second row of the table, 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 in turn 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: 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 operative, 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 (but keeping 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, in our model) and nominal rigidities (mostly sticky

prices) appear to be relevant factors in accounting for the evidence on the effects of technology shocks. By way of contrast, *both* nominal and real rigidities seem to be required to account for the empirical effects of monetary policy shocks (see, for example, Christiano, Eichenbaum, and Evans, 1999, or the dynamics of inflation, for example, Galí and Gertler, 1999).

## 6. Conclusion

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. 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. Those caveats 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 and labor input measures that is the hallmark of the business cycle.

## 7. Addendum: A Response to Ellen McGrattan

In her comments to the present paper, Ellen McGrattan (2004) dismisses the evidence on the effects of technology shocks based on structural VARs (SVARs) that rely on long-run identifying restrictions. The purpose of this addendum is to explain why we think McGrattan's analysis and conclusions are misleading. Since some of her argument and the evidence she provides is based on her recent working paper with Chari and Kehoe, our discussion often refers directly to their paper (Chari, Kehoe, and McGrattan, 2004a).

Our main point is easy to summarize. McGrattan and Chari, Kehoe, and McGrattan (CKM) study a number of model economies, all of which predict that hours should rise in response to a positive technology shock. Yet when they estimate an SVAR on data generated by

those models, the resulting impulse responses show a decline in hours in response to such a shock (with one exception, to be discussed below).

McGrattan presents her findings and those in CKM as an illustration of a general flaw with SVARs. But we find that conclusion unwarranted. What McGrattan and CKM really show is that a *misidentified* and/or *misspecified* SVAR often leads to incorrect inference. As McGrattan herself acknowledges, in her example of a standard RBC model (as well as in all but one of the examples in CKM), the assumptions underlying the data-generating model are inconsistent with the identifying assumption in the VAR: either technology is stationary, or nontechnology shocks have a permanent effect on productivity, or the order of integration of hours is wrong.<sup>51</sup> In those cases, the finding of incorrect inference is neither surprising nor novel since it restates points that have already been made in the literature.<sup>52</sup> That conclusion should be contrasted with that of Erceg, Guerrieri, and Gust (2004), who show that when the SVAR is correctly specified and the identifying restrictions are satisfied by the underlying data-generating models, the estimated responses to technology shocks match (at least qualitatively) the theoretical ones.

We think that, when properly used, SVARs provide an extremely useful guide for developing business-cycle theories. Evidence on the effects of particular shocks that is shown to be robust to a variety of plausible identification schemes should not be ignored when developing and refining DSGE models that will be used for policy analysis. On the one hand, that requirement imposes a stronger discipline on model builders than just matching the patterns of *unconditional* second moments of some time series of interest, the approach traditionally favored by RBC economists. On the other hand, it allows one to assess the relevance of alternative specifications without knowledge of all the driving forces impinging on the economy.<sup>53</sup>

Another finding in CKM that may seem striking to many readers is that their business accounting framework produces a rise in hours in response to a positive technology shock, in contrast with the evidence summarized in Section 2 of the present paper. Below, we conjecture that such a result hinges critically on treating the conventional Solow residual as an appropriate measure of technology, in contrast to the wealth of evidence suggesting the presence of significant procyclical error in that measure of technology. By way of contrast, most of the SVAR-based findings on the effects of technology shocks overviewed

in the present paper rely on identifying assumptions that are much weaker than those required for the Solow residual to be a suitable measure of technology.

Next, we elaborate on the previous points as well as on other issues raised by McGrattan's comment. First, we try to shed some light on why the estimated SVARs do not recover the model-generated impulse responses. Second, we provide a conjecture about why CKM's estimated model would predict an increase in hours in response to a positive technology shock, even if the opposite were true. Finally, we comment on CKM's proposed alternative to SVARs.

### *7.1 Why Does the SVAR Evidence Fail to Match the McGrattan and CKM Models' Predictions?*

The reason why the SVAR estimates reported by McGrattan fail to recover the joint response of output and hours implied by her RBC model should not be viewed as reflecting an inherent flaw in the SVAR approach. Instead, it is most likely a consequence of misspecification and misidentification of the SVAR used.

First, and most flagrantly, the geometric growth specification of technology assumed in the McGrattan exercise implies that technology shocks will have only temporary effects on labor productivity. A maintained assumption in Galí (1999) and in Section 2.1 above is the existence of a unit root in the technology process, underlying the observed unit root in productivity. It is clear that if a researcher holds an inherent belief in the stationarity of technology, she will not want to use that empirical approach to estimate the effects of technology shocks. We find the notion that technology shocks don't have permanent effects hard to believe, though we cannot offer any proof (and though we have provided suggestive evidence along those lines in Section 3.1). In any event, we find it useful to point out that the literature contains several examples, reviewed in Section 2, that do not rely on the unit root assumption and that yield results similar to Galí (1999).<sup>54</sup>

In principle, CKM appear to overcome the previous misidentification problem by using as a data-generating mechanism an RBC model that assumes a unit root in technology. They consider two versions of that model (preferred and baseline), which we discuss in turn. Their preferred specification fails to satisfy the identifying restriction of the VAR in another important dimension: because of the *endogeneity* of

technology in their model (reflected in the nonzero off-diagonal terms in the process describing the driving forces), shocks that are non-technological in nature are going to have an effect on the level of technology and hence on productivity. As a result, the identification underlying the SVAR will be incorrect, and inference will be distorted.

The two misidentification problems just discussed should not affect the CKM baseline specification because in the latter, technology is assumed to follow an *exogenous* random walk process. Yet when we look at the properties of that model, we uncover a *misspecification* problem in the VAR used. In a nutshell, and as is the case for most RBC models found in the literature, CKM's baseline model implies that hours worked follow a stationary process, though they estimate the SVAR using first-differenced hours. The potential problems associated with that misspecification were originally pointed out by CEV (2003) and have been discussed extensively in Section 3 of the present paper.<sup>55</sup>

CKM provide one example (the exception we were referring to above) in which the estimated SVAR satisfies both the key long-run identifying restriction (technology is exogenous and contains a unit root) and is correctly specified (hours are introduced in levels). In that case, and not surprisingly, the SVAR makes a correct inference: hours are estimated to rise in response to a technology shock, as the model predicts. While CKM acknowledge that fact, they instead focus on the finding that the estimated impulse response shows a nonnegligible bias. This is an interesting point, but it is not central to the controversy regarding the effects of technology shocks: the latter has focused all along on the estimated *sign* of the comovement of output and hours, not on the size of the responses. Nor is it novel: it is one of the two main findings in Erceg, Guerrieri, and Gust (2003), who already point out and analyze the role played by the slow adjustment of capital in generating that downward bias.

Neither McGrattan nor CKM emphasize Erceg, Guerrieri, and Gust's (EGG's) second main finding, which is highly relevant for their purposes: using both a standard RBC model and a new Keynesian model with staggered wage and price setting as data-generating mechanisms, they conclude that the estimated responses to a technology shock, using the same SVAR approach as in Galí (1999), look like the true responses to that shock in both models, at least from a qualitative viewpoint (leading to a rise in hours in the former case, and to a drop in the latter, in a way consistent with the models' predictions).

## 7.2 *Why Does the CKM Accounting Framework Predict a Rise in Hours?*

The framework used by McGrattan in Section 2.2 of her comment is unlikely to be recognized by most macroeconomists as a standard RBC model, the title of the subsection notwithstanding. Instead, it consists of a version of the business-cycle *accounting* framework originally developed in Chari et al. (2004b). That framework consists of a standard RBC model with four driving forces (or wedges, in their terminology). One of those driving forces, which enters the production function as a conventional productivity parameter, is interpreted as a technology shock. Two other driving forces are broadly interpreted as a labor market and an investment wedge. The fourth is government spending. After assuming functional forms for preferences and technology as well as a conventional calibration of the associated parameters conventional in the RBC literature, CKM estimate a VAR model for the four driving forces using time series for output, hours, investment, and government consumption.

Let us put aside some of the issues regarding the suitability of SVARs discussed in the previous section to turn to a different question: Why does the estimated CKM accounting framework predict an increase in hours in response to a positive technology shock? The interest of the question may be puzzling to some readers; after all, the CKM model looks like a standard RBC model augmented with many shocks. But that description is not accurate in a subtle, but important dimension: the disturbances/wedges in the CKM accounting framework are not orthogonal to each other, having instead a rich dynamic structure. Thus, nothing prevents, at least in principle, some of the nontechnology wedges from responding to a technology shock in such a way as to generate a negative comovement between output and hours in response to that shock. After all, the increase in markups following a positive technology shock is precisely the mechanism through which a model with nominal rigidities can generate a decline in hours.

Here, we can only speculate on the sources of the sign of the response of hours predicted by the CKM model. But a cursory look at the structure of the model, and the approach to uncovering its shocks, points to a very likely candidate for that finding: the CKM measure of the technology parameter corresponds to the gap between (log) GDP and a weighted average of (log) capital and (log) hours, with the weights based on average income shares. In other words, the CKM

measure of technology corresponds, for all practical purposes, to the conventional Solow (1957) residual. In adopting that approach to identification of technology, CKM are brushing aside two decades of research pointing to the multiple shortcomings of the Solow residual as a measure of short-run variations to technology, from Hall (1988) to BFK (1999). In the absence of any adjustments for market power, variable utilization of inputs, and other considerations, the Solow residual, as an index of technological change, is known to have a large (and highly procyclical) measurement error.

To illustrate this, consider an economy with a constant technology (and no capital) in which output and (measured) hours are linked according to the following reduced-form equilibrium relationship:

$$y_t = \alpha n_t$$

CKM's index of technology  $z_t$  would have been computed, using the Solow formula as:

$$z_t = y_t - s n_t$$

where  $s$  is the average labor income share. Under Solow's original assumptions,  $s = \alpha$ . But the existing literature provides a number of compelling reasons why in practice we will almost surely have  $\alpha > s$ . It follows that CKM's technology index can be written as:

$$z_t = (\alpha - s)n_t$$

thus implying a mechanical positive correlation between measured technology and hours.

The previous example is admittedly overstylized, but we think it illustrates the point clearly. Thus, it should come as no surprise if the estimated responses of the different wedges to innovations in that error-ridden measure of technology were to be highly biased and may indeed resemble the responses to a demand disturbance. In fact, the use of VARs based on either long-run restrictions (as in Galí, 1999) or purified Solow residuals (as in BFK, 1999) as well as the approach to model calibration in Burnside and Eichenbaum (1996) was largely motivated by that observation.

### 7.3 *Some Agreement*

We cannot conclude this addendum without expressing our agreement with CKM's proposed alternative approach to the identification and

estimation of technology (and other shocks), based on the specification of a “state representation and a set of identifying assumptions that nests the class of models of interest” and that can be “conveniently estimated with Kalman filtering” techniques. But this is precisely the approach that we have pursued in Section 5 of the present paper, following the footsteps of a number of authors referred to in that section (including the second author of the present paper).

In her comment, McGrattan criticizes the particular model that we choose to implement that approach (which she refers to as the triple-sticky model) on the grounds that it abstracts from capital accumulation. But our goal was not to develop a fully-fledged model, encompassing all relevant aspects of the economy, just to provide an illustration of a potentially fruitful approach to analyzing the role of different frictions in shaping the estimated effects of technology shocks. Other authors have provided a similar analysis using a richer structure that includes endogenous capital accumulation, among many other features. The models used in that literature allow (but do not impose) all sorts of frictions in a highly flexible way, and nest the standard RBC model as a particular case. Most important for our purposes here, some of those papers (see, for example, Smets and Wouters, 2003b) have analyzed explicitly the effects of technology shocks implied by their estimated models. In a way consistent with our findings above, those effects have been shown to imply a negative response of hours to a positive technology shock. McGrattan reports no comparable evidence for her triple-sticky model with investment, though we conjecture that the latter would imply a similar response.

## Notes

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1. Prescott (1996a).

2. See Blanchard and Quah (1989) and Galí (1999) for details.
3. It is precisely this feature that differentiates the approach to identification in Galí (1999) from that in Blanchard and Quah (1989). The latter authors used restrictions on long-run effects on output, as opposed to labor productivity. In the presence of a unit root in labor input, that could lead to the mislabeling as technology shocks of any disturbances that was behind the unit root in labor input.
4. With four lags, the corresponding  $t$ -statistics are  $-2.5$  and  $-7.08$ , the level and first-difference, respectively.
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. Notice that the distribution of the impact effect on hours assigns a zero probability to an increase in that variable.
7. See, e.g., King et al. (1988a) and Campbell (1994).
8. See also Francis and Ramey (2003a), among others, for estimates using higher dimensional VARs.
9. Blanchard (1989, p. 1158).
10. See the comment on Shea's paper by Galí (1998) for a more detailed discussion of that point.
11. 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).
12. An analogous but somewhat more detailed analysis can be found in Francis and Ramey (2003a).
13. Of course, that was also the traditional view regarding technological change, but one that was challenged by the RBC school.
14. 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.
15. We are grateful to Craig Burnside and Ellen McGrattan for providing the data.
16. A similar conclusion is obtained by Fisher (2003) using a related approach in the context of the multiple technology shock model described below.
17. In particular, we use their fully corrected series from their 1999 paper. When revising the present paper, BFK told us of an updated version of their technology series, extending the sample period through to 1996 and incorporating some methodological changes. The results obtained with the updated series were almost identical to the ones reported below.
18. That odds ratio increases substantially when an  $F$  statistic associated with a covariates ADF test is incorporated as part of the encompassing analysis.
19. 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%). In their bivariate, level specification model, that contribution is as high as 66 and 33%, respectively.

20. Given the previous observations, one wonders how an identical prior for both specifications could be assumed, as CEV do when computing the odds ratio.
21. Unfortunately, CEV do not include any statistic associated with the null of no trend in hours in their encompassing analysis. While it is certainly possible that one can get a  $t$  statistic as high as 8.13 on the time-squared term with a 13% frequency when the true model contains no trend (as their Montercarlo analysis suggests), it must surely be the case that such a frequency is much higher when the true model contains the quadratic trend as estimated in the data!
22. In fact, total hours was the series used originally in Galí (1999).
23. The finding of a slight short run decline in output was obtained in BFK (1999).
24. Pesavento and Rossi (2003) propose an agnostic procedure to estimate the effects of a technology shock that does not require taking a stance on the order of integration of hours. They find that a positive technology shock has a negative effect on hours on impact.
25. We thank Jonas Fisher for kindly providing the data on real investment price.
26. See the discussion in McGrattan (1999); Dotsey (2002); and Galí, López-Salido, and Vallés (2003), among others.
27. This would be consistent with any model in which velocity is constant in equilibrium. See Galí (1999) for an example of such an economy.
28. Such a reduced-form relationship would naturally arise as an equilibrium condition of a simple RBC model with productivity as the only state variable.
29. 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.
30. Throughout we assume that the condition  $\kappa(\phi_\pi - 1) + (1 - \beta)\phi_y > 0$  is satisfied. As shown by Bullard and Mitra (2002), that condition is necessary to guarantee a unique equilibrium.
31. This corresponds to the impact elasticity with respect to productivity and ignores the subsequent adjustment of capital (which is very small). The source is Table 3 in Campbell (1994), with an appropriate adjustment to correct for his (labor-augmenting) specification of technology in the production function (we need to divide Campbell's number by two-thirds).
32. A similar result can be uncovered in an unpublished paper by McGrattan (1999). Unfortunately, the author did not seem to notice that finding (or, at least, she did not discuss it explicitly).
33. The analysis in Galí, López-Salido, and Vallés (2003) has been 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.
34. A less favorable assessment is found in Chang and Hong (2003), who conduct a similar exercise using four-digit U.S. manufacturing industries, and rely on evidence of sectoral nominal rigidities based on the work of Bils and Klenow (2002).

35. 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.”

36. However, the existing literature on estimating general equilibrium 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.

37. A somewhat different estimation strategy is the one followed by Christiano, Eichenbaum, and Evans (2003); Altig et al. (2003); and Boivin and Giannoni (2003), who estimate general equilibrium models by matching a model’s implied impulse-response functions to the estimated ones.

38. Details can be found in an appendix available from the authors upon request.

39. Specifically, every household  $j$  maximizes the following utility function:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[ G_t \log(C_t^j - bC_{t-1}) - \frac{(N_t^j)^{1+\varphi}}{1+\varphi} \right]$$

subject to a usual budget constraint. The preference shock evolves, expressed in logs, as:

$$g_t = (1 - \rho_g)\bar{G} + \rho_g g_{t-1} + \varepsilon_t^g$$

40. See Smets and Wouters (2003a) for a derivation of the price- and wage-setting equations.

41. 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).

42. See Fernández-Villaverde and Rubio-Ramírez (2004).

43. If a random draw of the parameters is such that the model does not deliver a unique and stable solution, we assign a zero likelihood value, which implies that the posterior density will be zero as well. See Lubik and Schorfheide (2003a) for an estimated DSGE model allowing for indeterminacy.

44. Rabanal (2003) finds a similar result for an estimated DSGE model that is only slightly different from the one used here.

45. We have also conducted some subsample stability analyses, splitting the sample into pre-Volcker years and the Volcker–Greenspan era. While there were some small differences in estimated parameters across samples, none of the main conclusions of this section were affected.

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

47. A related analysis has been carried out independently by Smets and Wouters (2003b), albeit in the context of a slightly different DSGE model.

48. The posterior mean and standard deviations are based on the same sample that was used to obtain the second moments.

49. A similar pattern of responses of output and hours to a technology shock can be found in Smets and Wouters (2003b).
50. We use the method of Ingram, Kocherlakota, and Savin (1994) to recover the structural shocks. This method is a particular case of using the Kalman filter to recover the structural shocks. We assume that the economy is at its steady-state value in the first observation, rather than assuming a diffuse prior. By construction, the full set of shocks replicate the features of the model perfectly.
51. In the one case where the VAR is identified correctly, it yields the correct qualitative responses, though with some quantitative bias resulting from the inability to capture the true dynamics with a low-order VAR. This result has been shown in Erceg, Guerrieri, and Gust (2004).
52. See Cooley and Dwyer (1998) and Christiano et al. (2003), among others.
53. See Christiano et al. (2003) for an illustration of the usefulness of that approach.
54. See, for example, BFK (1999), Francis et al. (2003), and Pesavento and Rossi (2004).
55. CKM's discussion of that problem is somewhat obscured by their reference to "the insufficient number of lags in the VAR" as opposed to just stating that hours are overdifferenced. See also Marcet (2004) for a more general discussion of the consequences (or lack thereof) of overdifferencing.

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