Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?

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I estimate a decomposition of productivity and hours into technology and nontechnology components. Two results stand out: (a) the estimated conditional correlations of hours and productivity are negative for technology shocks, positive for nontechnology shocks; (b) hours show a persistent decline in response to a positive technology shock. Most of the results hold for a variety of model specifications, and for the majority of G7 countries. The picture that emerges is hard to reconcile with a conventional real-business-cycle interpretation of business cycles, but is shown to be consistent with a simple model with monopolistic competition and sticky prices. (*JEL* E32, E24)

Real-business-cycle (RBC) theory, exemplified by the work of Finn E. Kydland and Edward C. Prescott (1982) and its subsequent extensions, interprets the bulk of aggregate fluctuations observed in the postwar U.S. economy as being consistent with the competitive equilibrium of a neoclassical growth model augmented with a labor-leisure choice and exogenous technology shocks. In addition to its theoretical appeal, proponents of the RBC paradigm point to its successful empirical performance as a reason for taking seriously its account of the mechanisms through which shocks impact the economy and are propagated over time.

The present paper questions the usefulness of the type of evidence generally provided in support of RBC models, and which focuses on their apparent ability to match the patterns of *unconditional* second moments of key macroeconomic time series.[1] The main argument can be summarized as follows: in order to match some key second moments of the data RBC economists must allow for multiple sources of fluctuations; with the latter, however, the model yields predictions that are stronger than restrictions on the sign and/or pattern of *unconditional* second moments. In particular, it yields predictions in terms of *conditional* second moments, i.e., second moments conditional on a given source of fluctuations. In that context, an evaluation criterion based on the model's ability to match unconditional moments may be highly misleading: the model can do well according to that criterion and yet provide a highly distorted picture of the economy's response to each type of shock.

That general point is illustrated below in the context of a well-known anomaly associated

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[1] See Kydland and Prescott (1996) for a description of the approach to model evaluation found in much of the RBC literature, and Christopher A. Sims (1989, 1996) for a critical appraisal of that approach. Examples of attempts to evaluate RBC models by focusing on other dimensions of their predictions include Mark W. Watson (1993), Galí (1994), and Julio J. Rotemberg and Michael Woodford (1996).

with the basic RBC model, namely, its prediction of a high positive correlation between hours and labor productivity.[2] The source of that correlation lies at the root of the mechanism underlying macro fluctuations in that model: it reflects the shifts in the labor demand schedule caused by technology shocks (and, to a less extent, the induced capital accumulation), combined with an upward-sloping labor supply. As is well known, the above prediction stands in stark contrast with the near-zero (and often negative) correlation found in the data.[3] That observation led researchers to augment the model with nontechnology shocks, i.e., with shocks that act predominantly as labor-supply shifters, inducing a negative comovement between productivity and hours which could offset the positive correlation resulting from technology shocks. Examples of such additional driving forces found in the literature include shocks to government purchases (e.g., Lawrence J. Christiano and Martin Eichenbaum, 1992), and preference shocks (Valerie Bencivenga, 1992), among others. The resulting ''augmented'' models could in principle account for the near-zero correlation between hours and productivity without departing from the RBC paradigm and, in particular, without altering the model's predictions regarding the dynamic effects of technology shocks.

Alternative explanations to the productivity-hours anomaly that depart from the basic RBC paradigm in a more fundamental way do, however, exist. In Section I below I show how a stylized model with monopolistic competition, sticky prices, and variable effort can potentially explain the near-zero unconditional correlation between productivity and hours *while reversing its sources*: under plausible assumptions, the model predicts that technology shocks generate a *negative* comovement between those two variables, offset by the *positive* comovement arising from nontechnology shocks (monetary shocks, in the example economy).

An empirical evaluation of the two classes of models can exploit their different implications regarding the responses of hours and productivity *to each type of shock* and, as a result, their *conditional* correlations. With that goal in mind, I attempt to identify and estimate the components of productivity and labor-input variations associated with technology shocks on the one hand, and nontechnology shocks on the other. That decomposition is carried out using a structural vector autoregressive (VAR) model, identified by means of a long-run restriction which is satisfied by a broad range of models, including RBC models and ''new Keynesian'' models (as exemplified by the model in Section I). Section II contains a description of the empirical methodology, and of its connection with theoretical models of the business cycle.

Section III presents the results. The baseline evidence reported, based on postwar U.S. data, includes estimates of conditional correlations, as well as estimated impulse responses of output, hours, and productivity to technology and demand shocks. Several results stand out: (a) the estimated conditional correlations of hours and productivity are *negative* for technology shocks, *positive* for demand shocks; (b) the impulse responses show a persistent *decline* of hours in response to a *positive* technology shock; (c) measured productivity *increases* temporarily in response to a *positive* demand shock; (d) movements in output and hours attributed to demand shocks are strongly positively correlated, and account for the bulk of postwar business cycles; and (e) neither is true for the fluctuations attributed to technology shocks. Overall, the evidence seems to be clearly at odds with the predictions of standard RBC models, but largely consistent with the class of new Keynesian models exemplified by the framework in Section I. Those results, and many others, are shown to be robust to the labor-input measure used (hours or employment), and to the specification of the underlying structural VAR. Section III also reports related evidence based on data for the remaining G7 countries. Qualitatively, that evidence largely

[2] Henceforth I often use the shorter term *productivity* to refer to *average labor productivity*.

[3] See, e.g., Gary D. Hansen and Randall Wright (1992) for a discussion of the employment-productivity puzzle, as well as other anomalies regarding the labor-market predictions of RBC models.

mirrors the one obtained for the United States, with the main results holding for every G7 country but Japan.

In Section IV, I examine the implications of the estimated decomposition regarding the role played by technology shocks as sources of postwar business cycles. Section V explores possible ways of reconciling that evidence with the RBC paradigm. Finally, Section VI summarizes the main results of the paper and concludes.

I. Labor-Market Dynamics in a Sticky Price Model

In this section I develop and analyze a monetary model with monopolistic competition, sticky prices and variable labor effort.[4] I assume two exogenous driving forces: technology and monetary shocks. The focus of the analysis is on the joint response of productivity and hours to each of those disturbances. The model is deliberately stylized, in order to convey the basic point in the simplest possible way (in other words, it is *not* meant to provide a complete account of the mechanisms underlying business cycles). Thus, capital accumulation is ignored, and nominal price rigidities are introduced by having firms set their prices before shocks are realized. The assumptions on functional forms and statistical properties of the shocks make it possible to derive an exact closed-form representation of the equilibrium processes for the variables of interest in terms of the exogenous driving forces.

A. *Households*

The representative household seeks to maximize

$$E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \log C + \lambda_m \log \frac{M_t}{P_t} - H(N_t, U_t) \right\} \tag{1}$$

subject to the budget constraint

$$\int_0^1 P_{it} C_{it}\, di + M_t = W_t N_t + V_t U_t + M_{t-1} + \Upsilon_t + \Pi_t$$

for $t = 0, 1, 2, \ldots$. C_t is a composite consumption index defined by

$$C_t = \left(\int_0^1 (C_{it})^{\varepsilon - 1/\varepsilon}\, di \right)^{\varepsilon/\varepsilon - 1}$$

where C_{it} is the quantity of good $i \in [0, 1]$ consumed in period t, and $\varepsilon > 1$ is the elasticity of substitution among consumption goods. The price of good i is given by P_{it}, and

$$P_t = \left(\int_0^1 (P_{it})^{1-\varepsilon}\, di \right)^{1/1-\varepsilon}$$

is the aggregate price index. M denotes (nominal) money holdings. Function H measures the disutility from work, which depends on hours (N) and effort (U). The following functional form is assumed

$$H(N_t, U_t) = \frac{\lambda_n}{1+\sigma_n} N_t^{1+\sigma_n} + \frac{\lambda_u}{1+\sigma_u} U_t^{1+\sigma_u}.$$

Υ and Π denote, respectively, monetary transfers and profits. W and V denote the (nominal) prices of an hour of work and a unit of effort, respectively. $\beta \in (0, 1)$ is the discount factor. λ_m, λ_n, λ_u, σ_n, σ_u, are positive constants.

The first-order conditions associated with the household problem are

$$C_{it} = \left(\frac{P_{it}}{P_t} \right)^{-\varepsilon} C_t \tag{2}$$

[4] Recent examples of dynamic general equilibrium models of the business cycle with nominal rigidities include Jean-Olivier Hairault and Franck Portier (1993), Jean-Pascal Bénassy (1995), Jang-Ok Cho and Thomas Cooley (1995), Jinill Kim (1996), Robert G. King and Alexander L. Wolman (1996), and Rotemberg (1996). Examples of business-cycle models with variable effort and/or utilization can be found in Craig Burnside et al. (1993) and Mark Bils and Cho (1994). Robert J. Gordon (1990), Argia M. Sbordone (1995), Susanto Basu (1996), and Matthew D. Shapiro (1996), among others, discuss the implications of that phenomenon for the cyclical behavior of productivity measures.

$$\frac{1}{C_t} = \lambda_m \frac{P_t}{M_t} + \beta E_t\left[\frac{1}{C_{t+1}} \frac{P_t}{P_{t+1}}\right] \tag{3}$$

$$\frac{W_t}{P_t} = \lambda_n C_t N_t^{\sigma_n} \tag{4}$$

$$\frac{V_t}{P_t} = \lambda_u C_t U_t^{\sigma_u}. \tag{5}$$

B. *Firms*

There is a continuum of firms distributed uniformly on the unit interval. Each firm is indexed by $i \in [0, 1]$, and produces a differentiated good with a technology

$$Y_{it} = Z_t L_{it}^{\alpha}.$$

L_i may be interpreted as the quantity of *effective* labor input used by the firm, which is a function of hours and effort:

$$L_{it} = N_{it}^{\theta} U_{it}^{1-\theta}$$

where $\theta \in (0, 1)$.[5] Z is an aggregate technology index, whose growth rate is assumed to follow an independently and identically distributed (i.i.d.) process $\{\eta_t\}$, with $\eta_t \sim N(0, s_z^2)$. Formally,

$$Z_t = Z_{t-1} \exp(\eta_t).$$

At the end of period $t - 1$ (i.e., before period t's realization of the money supply and technology is observed) firm i sets the price P_{it} at which it will be selling good i during period t, taking as given the aggregate price level P_t. Once the shocks are realized, each firm chooses N_{it} and U_{it} optimally, given W_t and V_t. Given an output level Y_{it}, cost minimization requires

$$\frac{U_{it}}{N_{it}} = \left(\frac{1-\theta}{\theta}\right) \frac{W_t}{V_t}. \tag{6}$$

Furthermore, as long as the marginal cost is below the (predetermined) price P_{it}, each firm will find it optimal to accommodate any changes in the demand for its product, and will thus choose an output level

$$Y_{it} = \left(\frac{P_{it}}{P_t}\right)^{-\varepsilon} C_t. \tag{7}$$

Hence, when setting the price the firm will seek to maximize

$$\max_{P_{it}} E_{t-1}\{(1/C_t)(P_{it}Y_{it} - W_t N_{it} - V_t U_{it})\}$$

subject to (6) and (7). The corresponding first-order condition is given by

$$E_{t-1}\{(1/C_t)(\alpha\theta P_{it} Y_{it} - \mu W_t N_{it})\} = 0 \tag{8}$$

where $\mu \equiv \varepsilon/\varepsilon - 1$.[6]

C. *Monetary Policy*

The quantity of money M^s in the economy is assumed to evolve according to

$$M_t^s = M_{t-1}^s \exp(\xi_t + \gamma\eta_t) \tag{9}$$

where $\{\xi_t\}$ is a white noise process orthogonal to $\{\eta_t\}$ at all leads and lags, with $\xi_t \sim N(0, s_m^2)$. Notice that whenever $\gamma \neq 0$, the monetary authority is assumed to respond in a systematic fashion to technology shocks.

D. *Equilibrium*

In a symmetric equilibrium all firms will set the same price P_t and choose identical output, hours, and effort levels Y_t, N_t, U_t. Goods market clearing requires $C_t = C_{it} = Y_{it} = Y_t$, for all $i \in [0, 1]$, and all t. Equilibrium in the money market implies $M_t/M_{t-1} = \exp(\xi_t + \gamma\eta_t)$, for all t. Using both market-clearing conditions, one can rewrite (3) (after some algebraic manipulation) as

[5] Notice that we can write $L_{it} = N_{it}(U_{it}/N_{it})^{1-\theta}$, which implies that effective labor input is proportional to hours (as in the standard model) whenever effort per hour is constant.

[6] Notice that in the absence of uncertainty (8) simplifies to $P_{it} = \mu(W_t N_{it}/\alpha\theta Y_{it})$, which is just the familiar optimal price condition for a monopolist facing an isoelastic demand schedule.

$$C_t = \Phi \frac{M_t}{P_t} \tag{10}$$

where $\Phi \equiv \lambda_m^{-1}[1 - \beta \exp\{{}^1\!/\!{}_2(s_m^2 + \gamma^2 s_z^2)\}]$.[7] Furthermore, (4), (5), and (6) imply $U_t = A^{1/\alpha(1-\theta)} N_t^{(1+\sigma_n)/(1+\sigma_u)}$, where $A \equiv [\lambda_n(1 - \theta)/\lambda_u\theta]^{\alpha(1-\theta)/(1+\sigma_u)}$. That result allows us to write the following reduced-form equilibrium relationship between output and employment:

$$Y_t = AZ_t N_t^{\varphi} \tag{11}$$

where $\varphi \equiv \alpha\theta + \alpha(1-\theta)(1+\sigma_n)/(1+\sigma_u)$.

Finally, evaluating (4) and (8) at the symmetric equilibrium and combining them with (11) and (10) one can derive a set of expressions for the equilibrium levels of prices, output, employment, and productivity, in terms of the exogenous driving variables. Letting lower-case letters denote the natural logarithm of each variable, and dropping uninteresting constants, we have:

$$\Delta p_t = \xi_{t-1} - (1-\gamma)\eta_{t-1} \tag{12}$$

$$\Delta y_t = \Delta\xi_t + \gamma\eta_t + (1-\gamma)\eta_{t-1} \tag{13}$$

$$n_t = \frac{1}{\varphi}\,\xi_t - \frac{1-\gamma}{\varphi}\,\eta_t \tag{14}$$

$$\begin{aligned}\Delta x_t = {} & \left(1 - \frac{1}{\varphi}\right)\Delta\xi_t \\ & + \left(\frac{1-\gamma}{\varphi} + \gamma\right)\eta_t \\ & + (1-\gamma)\left(1 - \frac{1}{\varphi}\right)\eta_{t-1}\end{aligned} \tag{15}$$

where $x \equiv y - n$ is the log of (measured) labor productivity.

[7] We assume $\beta \exp\{{}^1\!/\!{}_2(s_m^2 + \gamma^2 s_z^2)\} < 1$. The constant velocity associated with (10) is a consequence of our assumption of i.i.d. money growth rates, which in turn implies a constant nominal rate.

The equilibrium responses of p, y, n, and x to each shock, represented by (12)–(15), are discussed next. A *monetary shock* has a transitory impact on output, employment, and productivity, and a permanent effect on the price level. More specifically, and in response to an unanticipated monetary expansion ($\xi_t > 0$), output and employment go up, reverting back to their original level after one period. The sign of the (also transitory) response of labor productivity x depends on the size of φ, and is positive whenever $\varphi > 1$. As made clear by (11), the latter condition corresponds to the notion of ''short-run increasing returns to labor'' emphasized in the literature on the cyclical behavior of productivity (e.g., Gordon, 1990). For that condition to be satisfied we require: (a) sufficiently ''productive'' effort (low θ), (b) a sufficiently low elasticity of effort's marginal disutility relative to that of employment ($\sigma_u \ll \sigma_n$), and (c) a sufficiently high elasticity of output with respect to effective labor input (high α). Finally, note that the only variable that is permanently affected by the exogenous increase in the money supply will be the price level, which will adjust proportionally (though with a one-period lag).

A (positive) *technology shock* ($\eta_t > 0$) has a permanent, one-for-one effect on output and productivity, as can be seen in (13) and (15). The same shock will have a permanent negative effect on the price level as long as $\gamma < 1$, i.e., if the degree of monetary accommodation is not too strong. Most interestingly, if the same condition is satisfied, a *positive* technology shock will have a *negative* short-run effect on the level of employment. The intuition for that result is straightforward. Consider, for the sake of exposition, the $\gamma = 0$ case (exogenous money). In that case, the combination of a constant money supply and predetermined prices implies that real balances (and, thus, aggregate demand) remain unchanged in the period when the technology shock occurs. Each firm will thus meet its demand by producing an unchanged level of output. If the technology shock is positive, producing the same output will require less labor input, and a decline in hours will be observed. Clearly, the sign of that short-run response of hours to a technology shock stands in stark contrast with the predictions of the basic RBC model. Furthermore, unchanged output and lower hours will lead to an unambiguous increase in measured labor productivity in response to the same shock. In the following period, firms adjust their prices downward (since marginal cost is lower), aggregate demand and output will go up, and employment returns to its original level. The sign of the associated change in labor productivity depends again on whether φ is greater or less than one (i.e., on whether the change in output is more or less than proportional to the change in hours), which, in turn, determines whether the immediate response of productivity to a technology shock overshoots or not its long-run level. By looking at (12)–(15) it should be clear that the *qualitative* effects of a technology shock described above will remain unchanged so long as $\gamma \in [0, 1)$, a parameter range which includes both exogenous monetary policy as well as a monetary rule aimed at smoothing price and employment changes.[8]

It is important to stress that the possibility of a decline in hours in response to a positive technology shock does not hinge on the assumptions of predetermined prices or absence of capital accumulation, both made here for expository convenience. Thus, Rotemberg (1996) obtains a similar response in a model with quadratic costs of price adjustment, and for sufficiently high values of the parameter indexing the magnitude of those costs. A similar response is found in King and Wolman (1996) in a similar model with capital accumulation and a price-setting structure originally found in Guillermo Calvo (1983). Finally, King and Watson (1996) also report a negative contemporaneous correlation between multifactor productivity and hours in their calibrated sticky price model with capital accumulation.

The *unconditional* covariances among the growth rates of output, labor productivity, and employment implied by the above model are easily computed using (12)–(15):

$$\text{(16)} \quad \operatorname{cov}(\Delta y_t, \Delta n_t) = \frac{2s_m^2 + (1-\gamma)(1-2\gamma)s_z^2}{\varphi}$$

$$\text{(17)} \quad \operatorname{cov}(\Delta y_t, \Delta x_t) = \frac{2(\varphi-1)s_m^2 + (\gamma+\varphi-1)s_z^2}{\varphi}$$

$$\text{(18)} \quad \operatorname{cov}(\Delta n_t, \Delta x_t) = \frac{2(\varphi-1)s_m^2}{\varphi^2} - \frac{(1-\gamma)\,[(2-\varphi)+2\gamma(\varphi-1)]s_z^2}{\varphi^2}.$$

Whenever $\gamma \in [0, 1/2)$ and/or exogenous monetary shocks are a sufficiently important (relative to technology), the model predicts that hours growth should be procyclical—a property which is a robust feature of the data. Furthermore, $\varphi > 1$ is a sufficient condition for measured labor productivity to be procyclical—another strong feature of the data—independently of the relative importance of the two shocks.

The sign of the comovement between hours and productivity growth—the focus of our attention—depends on the size of φ, the policy parameter γ, and the relative importance of shocks. It is useful to look first at the sign of the *conditional* covariances. Letting $\operatorname{cov}(\Delta n_t, \Delta x_t | z)$ denote the covariance between Δn_t and Δx_t *conditional on technology being the only source of fluctuations*, we have:

$$\operatorname{cov}(\Delta n_t, \Delta x_t | z) = -\frac{(1-\gamma)}{\varphi^2}[(2-\varphi)+2\gamma(\varphi-1)]s_z^2.$$

Under the assumptions $\gamma \in [0, 1)$ and $\varphi \in (1, 2)$ it is easy to check that $\operatorname{cov}(\Delta n_t, \Delta x_t | z) < 0$, i.e., technology shocks generate a negative comovement between hours and productivity growth. On the other hand, the

[8] More generally, the choice of the policy rule will only have a permanent effect on prices, but it will affect the size and/or the dynamic pattern of the responses of output, employment, and productivity. In particular, the monetary authority will face a trade-off between employment and price volatility.

analogous covariance *conditional on monetary shocks being the only source of fluctuations*, denoted by $\text{cov}(\Delta n_t, \Delta x_t | m)$, is given by

$$\text{cov}(\Delta n_t, \Delta x_t | m) = \frac{2(\varphi - 1)}{\varphi^2} s_m^2$$

whose sign depends the size of φ. If $\varphi > 1$, monetary shocks will generate a positive comovement between the same variables.

The case of most interest—and a plausible one, in my view—corresponds to $\varphi \in (1, 2)$, and $\gamma \in [0, 1)$, i.e., it combines some ''short-run increasing returns to labor'' with a not-too-strong endogenous money response. In that case the model's predictions regarding the signs of the *unconditional* comovements among output, hours, and productivity are consistent with the evidence, and potentially close to those predicted by standard RBC models. Yet the two models have very different implications regarding the *conditional* comovements between hours and productivity growth. In particular, if technology shocks are the only source of fluctuations, the sticky price model predicts a *negative* correlation between hours and productivity growth, whereas the corresponding comovement conditioned on the nontechnology shocks is *positive*. Such a result is in stark contrast with the prediction of standard RBC models with multiple shocks where, for the reasons described in the introduction, technology shocks are a source of a positive comovement between hours and productivity, while nontechnology shocks generate a negative comovement.

Next I propose a simple empirical framework that allows me to estimate the conditional correlations in the data, and thus assess the relative merits of the two classes of models.

II. An Empirical Model

In order to estimate their conditional comovements, the components of hours and productivity variations associated with technology and nontechnology shocks must be disentangled. My approach involves the use of a structural VAR model, identified by the restriction that only technology shocks may have a permanent effect on the level of productivity. As argued below, that restriction is satisfied by a broad range of models, including RBC models, and models with nominal rigidities. The *conditional* correlations of hours and productivity variations can then be computed using the estimated coefficients of the structural moving average (MA) representation.

A. *Assumptions Underlying the Identification Strategy*

Next I discuss three assumptions which are jointly sufficient to yield the identifying restriction used, and which implicitly determine the range of models that the framework below can embrace.

ASSUMPTION 1: *Output is determined according to a homogeneous of degree one, strictly concave, aggregate production function*

$$Y_t = F(K_t, Z_t L_t) \tag{19}$$

where Y is output, K and L denote the *effective* capital and labor-input services employed (thus allowing for possible unobservable variations in the utilization rate of both inputs), and Z is an *exogenous* technology parameter following a stochastic process with a unit root (i.e., some technology shocks have permanent effects on the level of Z).

ASSUMPTION 2: *The capital-labor ratio (measured in efficiency units) K_t/Z_tL_t follows a stationary stochastic process.*

The previous assumption is not hard to justify. Letting r_t denote the return on physical capital, profit maximization (combined with Assumption 1 and other standard assumptions) implies

$$r_t = \frac{F_K\left(\dfrac{K_t}{Z_t L_t}, 1\right)}{\text{markup}} - \text{depreciation rate.} \tag{20}$$

Thus, under the maintained assumption of stationarity (or constancy) of the markup and the depreciation rate, the capital-labor ratio will be stationary whenever the sequence of returns $\{r_t\}$ is stationary.[9] The latter property is consistent with most dynamic models of the business cycle, which display fluctuations around a steady state (or balanced growth path) that corresponds to that of the Ramsey-Cass-Koopmans model or the Solow-Swan model.[10] Most importantly, that assumption also appears to be consistent with the empirical characterizations of the time-series properties of asset returns found in the literature.[11]

ASSUMPTION 3: *Effective labor input L_t is a homogeneous of degree one function of hours and effort*:

$$L_t = g(N_t, U_t) \tag{21}$$

and effort per hour U_t/N_t follows a stationary stochastic process.

Homogeneity is required if effective labor input is to be proportional to hours whenever effort per hour is constant. Stationarity of U_t/N_t seems empirically plausible and is certainly consistent with existing business-cycle models with variable effort (e.g., Burnside et al. [1993], or the model of Section I).

Combining Assumptions 1–3 one can derive the following expression for *measured* labor productivity:

$$X_t = \frac{Y_t}{N_t} = \frac{Y_t}{L_t}\frac{L_t}{N_t} = Z_t F\left(\frac{K_t}{Z_t L_t}, 1\right) g\left(1, \frac{U_t}{N_t}\right)$$

or, taking logs,

$$x_t = z_t + \zeta_t \tag{22}$$

where $\zeta_t \equiv \log F(K_t/Z_tL_t, 1)\, g(1, U_t/N_t)$ is stationary under the above assumptions. Equation (22) holds the key to the identification of technology shocks, for it implies that *only* permanent changes in the stochastic component of the technology parameter z can be the source of the unit root in productivity. Put it differently, under the assumptions above, *only technology shocks can have a permanent effect on the level of labor productivity,* even though any other shock impinging on the economy can affect labor productivity temporarily through its effects on effort per hour and the capital-labor ratio.[12]

The previous condition provides the key identifying restriction in the structural VAR model estimated here. Notice that such a restriction allows both types of shocks to have permanent effects on the levels of hours and output, and thus does not ''mislabel'' as technology any other shock that may have such permanent effects.[13] From that viewpoint my identifying restriction is different from the one originally proposed by Blanchard and Danny Quah (1989), and which restricted demand shocks (in their terminology) not to have permanent effects on the level of output. Also, notice that in contrast with Shapiro and Watson (1988) I do not restrict technology shocks *not* to have permanent effects on hours. Though with a different motivation and objectives, the identification strategy adopted here

[9] Clearly, the same property would hold if we were to allow for adjustment costs or any other departure from (20), as long as the stochastic component of that deviation was stationary.

[10] Alternatively, one could have assumed stationarity of the capital-output ratio, as in Shapiro and Watson (1988). Combined with (19), either assumption corresponds to a stationary real rate.

[11] The evidence on stock returns points to small departures from white noise (see, e.g., Kenneth J. Singleton, 1990). The evidence on real interest rates is less strong, but generally tends to reject the presence of a unit root (see, e.g., Frederic S. Mishkin, 1992), and the evidence reported below).

[12] The investment-specific form of technological change assumed in Jeremy Greenwood et al. (1997) is not nested in the present framework, though it is easy to check that the identifying restriction proposed here would also hold in a version of their model with a unit root in the investment-specific technology parameter (i.e., the relative price of equipment), since the capital-labor ratio (and thus labor productivity) is fully pinned down by the (stationary) interest rate and the value of that technology parameter.

[13] Examples of such shocks include permanent changes in government purchases (Marianne Baxter and King, 1993), permanent labor-supply shocks (Shapiro and Watson, 1988), or even monetary shocks in an insider-outsider model of the labor market (Olivier J. Blanchard and Lawrence H. Summers, 1986).

is closer to that in Edward N. Gamber and Frederick L. Joutz (1993), who restrict labor-supply shocks not to have a permanent effect on real wages, while allowing labor- demand/technology shocks to have such a permanent effect.

B. *Specification and Conditional Correlations Estimators*

My empirical model interprets the observed variations in (log) productivity (x_t) and (log) hours (n_t) as originating in two types of exogenous disturbances—technology and non-technology shocks—which are orthogonal to each other, and whose impact is propagated over time through various unspecified mechanisms. That idea is formalized by assuming that the vector $[\Delta x_t, \Delta n_t]'$ can be expressed as a (possibly infinite) distributed lag of both types of disturbances:

$$(23)\quad \begin{bmatrix} \Delta x_t \\ \Delta n_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^m \end{bmatrix} \equiv \mathbf{C}(L)\varepsilon_t$$

where $\{\varepsilon_t^z\}$ and $\{\varepsilon_t^m\}$ denote, respectively, the sequences of technology and non-technology shocks. The orthogonality assumption (combined with a standard normalization) implies $E\varepsilon_t\varepsilon_t' = I$. Furthermore, the identifying restriction that the unit root in productivity originates exclusively in technology shocks corresponds to $C^{12}(1) = 0$. In other words, the matrix of long-run multipliers $\mathbf{C}(1)$ is assumed to be lower triangular.

The specification in (23) is based on the assumption that both productivity and hours are integrated of order one, so that first-differencing of both variables is necessary to achieve stationarity. That assumption is motivated by the outcome of standard augmented Dickey Fuller (ADF) tests which do not reject the null of a unit root in the levels of either series, but do reject the same null when applied to the first-differences (at the 5-percent significance level).[14] Notice that while my identification strategy hinges critically on the presence of a unit root in productivity, it can accommodate both $I(0)$ and $I(1)$ hours. Thus, and in order to check the robustness of the results, I also estimate an analogous model for $[\Delta x_t, \hat{n}_t]'$, where $\hat{n}_t$ denotes deviations of (log) hours from a fitted linear time trend.

Consistent estimates of the coefficients of $\mathbf{C}(L)$ in (23) are obtained as functions of the estimated parameters of a reduced-form VAR for $[\Delta x_t, \Delta n_t]'$, following a standard procedure.[15] Given an estimate for $\mathbf{C}(L)$ (which embeds the impulse response coefficients), estimates of conditional correlations can be obtained using the following formula (with the population coefficients are replaced by their corresponding estimates):

$$(24)\quad \rho(\Delta x_t, \Delta n_t | i) = \frac{\sum_{j=0}^{\infty} C_j^{1i} C_j^{2i}}{\sqrt{\mathrm{var}(\Delta x_t | i)\mathrm{var}(\Delta n_t | i)}}$$

for $i = z, m$, where $\mathrm{var}(\Delta x_t | i) = \sum_{j=0}^{\infty} (C_j^{1i})^2$ and $\mathrm{var}(\Delta n_t | i) = \sum_{j=0}^{\infty} (C_j^{2i})^2$ are conditional variances of hours and productivity growth.[16]

III. Evidence

This section reports and discusses the evidence on conditional productivity-labor input comovements. First, I report evidence based on a bivariate model estimated using postwar U.S. data. Then I show how the main qualitative results obtained in that benchmark model also hold for an augmented model that includes a number of monetary and financial

[14] Tables with a detailed description of unit root tests can be found in Galí (1996a) or in the Appendix available upon request.

[15] Detailed formulas for consistent estimator of $C(L)$ in VAR models with recursive long-run restrictions can be found in Galí (1996b) or in the Appendix available upon request.

[16] Of course, in practice the sums in (24) are truncated at a large (but finite) lag.

variables (in addition to productivity and labor-input measures), as well as for most of the remaining G7 countries.

A. *Evidence from a Bivariate Model*

The bivariate model (23) is estimated using U.S. quarterly data covering the period 1948:1–1994:4. The baseline series for labor input is the log of total employee-hours in nonagricultural establishments (''hours''). The baseline series for labor productivity was constructed by subtracting the previous variable from the log of GDP. In addition, I also report results obtained using the log of the employed civilian labor force (''employment'') as a labor-input measure, with the corresponding productivity measure constructed analogously. All series were drawn from Citibase.

Table 1 reports estimates of both unconditional and conditional correlations between the growth rates of each labor-input measure and the corresponding measure of productivity. Standard errors are reported in parentheses, and significant estimates highlighted with one (10-percent level) or two (5-percent level) asterisks.[17] The first panel reports results based on an estimated VAR model for $[\Delta x_t, \Delta n_t]'$, with the second panel reporting the corresponding results based on the $[\Delta x_t, \hat{n}_t]'$ specification.

Estimates of the unconditional correlation of labor input and productivity are small, slightly negative, and only significant when hours are used. As argued in Christiano and Eichenbaum (1992) the absence of a large positive correlation between those variables conflicts with a key prediction of the basic RBC model driven by technology shocks, but can in principle be reconciled with multiple-shock versions of the same model, since non-technology shocks are predicted to generate a negative correlation that may offset the positive comovement induced by technology shocks. Our benchmark estimates of the *conditional* correlations—reported in the second and third columns—are, however, inconsistent with that explanation: in all cases, the estimates point to a large *negative* correlation between the technology-driven components of labor input and productivity growth, whereas the corresponding nontechnology components display a *positive* correlation. Furthermore, and with the exception of the specification using detrended employment, all the estimates are statistically significant at conventional levels. Figure 1 provides a graphical counterpart to the previous evidence, by displaying scatterplots of the original productivity and hours series (in growth rates), as well as their technology and nontechnology components recovered from the identified VAR.[18]

The previous results are, however, consistent with the predictions of models with imperfect competition, sticky prices, and variable effort, as exemplified by the stylized model developed in Section I. As shown there, the short-term rigidity in aggregate demand resulting from the stickiness of the price level leads technology shocks to generate a negative comovement between hours and productivity, while unobserved effort variations can account for the positive comovement induced by demand shocks.

In order to understand the source of the previous results it is useful to look at the estimated dynamic responses of productivity, output, and hours to each type of shock. Figure 2 displays the estimated impulse responses based on the model with first-differenced hours, together with their associated two-standard error confidence bands. In response to a positive technology shock of size equal to one-standard deviation, labor productivity experiences an immediate increase of about 0.6 percent, eventually stabilizing at a level somewhat higher. Output also experiences a permanent increase, but the initial rise appears to be more gradual than that of productivity. The gap between the

[17] Standard errors for conditional correlations and impulse responses were computed using a Monte Carlo method to sample from the estimated asymptotic distribution of the VAR coefficients and the covariance matrix of the innovations. Reported standard errors correspond to the standard deviation of each statistic across 500 draws.

[18] The dramatic contrast between those estimates and the predictions of standard RBC model can be by comparing Figure 1 here to Charts 2 and 4 in Hansen and Wright (1992).

TABLE 1—CORRELATION ESTIMATES: BIVARIATE MODEL

	Unconditional	Conditional	
		Technology	Nontechnology
Panel A: First-differenced labor			
Hours	−0.26**	−0.82**	0.26**
	(0.08)	(0.12)	(0.12)
Employment	−0.02	−0.84**	0.64**
	(0.07)	(0.26)	(0.13)
Panel B: Detrended labor			
Hours	−0.26**	−0.81**	0.35*
	(0.08)	(0.11)	(0.20)
Employment	−0.02	−0.35	0.38
	(0.07)	(0.49)	(0.56)

Notes: Table 1 reports estimates of unconditional and conditional correlations between the growth rates of productivity and labor input (hours or employment) in the United States, using quarterly data for the period 1948:1–1994:4. Standard errors are shown in parentheses. Significance is indicated by one asterisk (10-percent level) or two asterisks (5-percent level). Conditional correlation estimates are computed using the procedure outlined in the text, and on the basis of an estimated bivariate VAR for productivity growth and labor-input growth (Panel A) or productivity growth and detrended labor input (Panel B). Data sources and definitions can be found in the text.

initial increase in labor productivity and the (smaller) increase in output is reflected in a short-lived, though persistent (and significant), decline in hours. The fact that the bulk of the joint variation in employment and productivity arising from a technology shock takes place on impact, with both variables moving in opposite directions, is largely responsible for the negative conditional correlation reported above.[19]

Figure 2 also displays the estimated dynamic responses to a nontechnology shock, as identified by the empirical framework above. Such a shock is shown to have a persistent positive effect on output, hours, and productivity. Interestingly, while the effect on productivity vanishes over time (by assumption), the shock has a sizable (and statistically significant) permanent impact on both hours and output, thus emerging as the main source of the unit root detected in hours. The large positive comovement of productivity and hours on impact is the main source of the positive sign in the estimated correlation conditional on nontechnology shocks reported in Table 1.

Most of the qualitative patterns in the impulse responses just presented are preserved when detrended hours (i.e., deviations of log hours from a fitted linear time trend) are used in the estimated VAR, as displayed in Figure 3. The only significant difference lies in the absence (by construction) of a permanent effect of the nontechnology shock on the level of hours (and, consequently, on output, given the identifying restriction). Furthermore, similar results (not reported) obtain when employment is used instead of hours as a labor-input measure.[20]

[19] A decline in hours (or, alternatively, an increase in unemployment) resulting from a positive technology shock can also be detected in other structural VARs in the literature. Since the purpose of those exercises is generally unrelated to the issue at stake here, the presence of such a result often appears to go unnoticed or, at most, is briefly mentioned in the text. Some of the papers where that result can be found are: Blanchard (1989 Figure 1.b), Blanchard and Quah (1989 Figure 6), Gamber and Joutz (1993 Figure 1), Blanchard et al. (1995 Figures C and D), Cooley and Mark Dwyer (1995 Figure 1), and Mario Forni and Lucrezia Reichlin (1995 Figure 3). The latter two papers provide a longer discussion of the finding, interpreting it as being consistent with the traditional Keynesian model.

[20] Impulse responses using employment data can be found in Galí (1996a Figure 3.b) and in the Appendix available upon request.

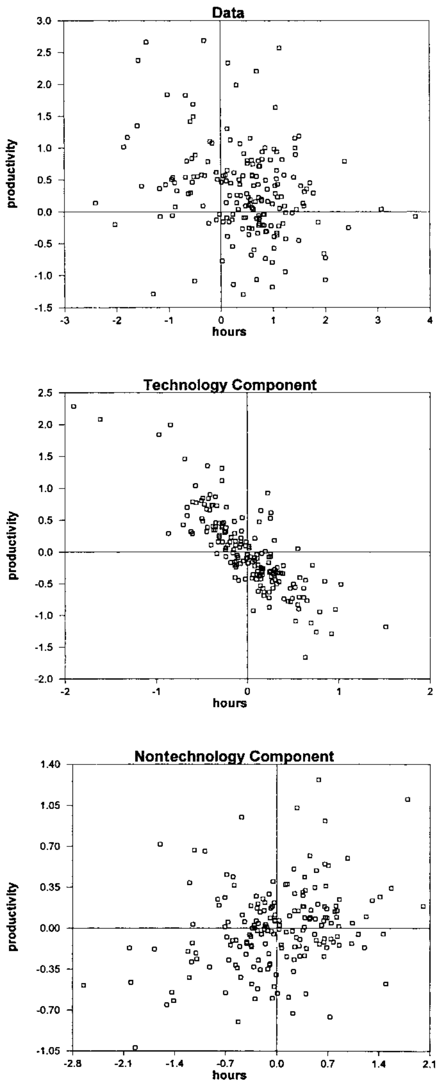

FIGURE 1. PRODUCTIVITY VS. HOURS: DATA, TECHNOLOGY COMPONENT, AND NONTECHNOLOGY COMPONENT

B. *Evidence from a Five-Variable Model*

As a robustness check I estimate a higher dimensional (five-variable) VAR model, which allows for four orthogonal nontechnology shocks—still identified as shocks that do not have a permanent effect on the level of labor productivity. Even though I make no attempt to identify each of those shocks separately (which would require imposing additional, possibly controversial, restrictions), the estimated model provides interesting information regarding the effects of technology shocks on a larger number of variables than was the case for the bivariate VAR.

The specification considered uses data on money, interest rates, and prices, in addition to the productivity and labor-input series used in the bivariate model. My measure of the stock of money, denoted by m, is the (log) of M2. The price measure (p) is the (log) of the consumer price index (CPI). The nominal interest rate (r) is the three-month Treasury Bill rate. Because of limited availability of M2 data the sample period begins at a later date (59:1–94:4).

In preliminary data analysis, standard ADF tests did not reject the null of a unit root in money growth (Δm), inflation (Δp), and the nominal rate (r) at a 5-percent significance level, but did reject the same hypothesis for their respective first-differences, as well as for $\Delta(m_t - p_t)$ (the growth rate of real balances), as well as $r_t - \Delta p_t$ (the real interest rate).[21] That characterization suggests estimating a VAR model for $[\Delta x_t, \Delta n_t, \Delta m_t - \Delta p_t, r_t - \Delta p_t, \Delta^2 p_t]'$.[22] Using the estimated VAR, together with the assumption that only technology shocks have a permanent effect on x, and the orthogonality between technology and nontechnology shocks, one can recover estimates of the dynamic responses to a technology shock, as well as the components of the variation in each time series associated with those shocks and—as a residual—the sum of the components driven by the remaining four nontechnology shocks.

[21] That characterization is consistent with the findings of many other authors (see, e.g., Shapiro and Watson [1988] and Galí [1992]). Details of the tests can be found in Table 1 of Galí (1996a) and in the Appendix available upon request.

[22] As a robustness check to make sure that none of the qualitative results hinged on the cointegration assumptions implicit in the specification of the VAR, I repeated the exercise using the estimates of a VAR ''in first-differences'' (as would be appropriate in the absence of cointegration), i.e., a VAR for the five-variable vector $[\Delta x_t, \Delta n_t, \Delta^2 m_t, \Delta r_t, \Delta^2 p_t]'$. The results obtained were very similar to those reported in the text, and can be found in the Appendix available upon request.

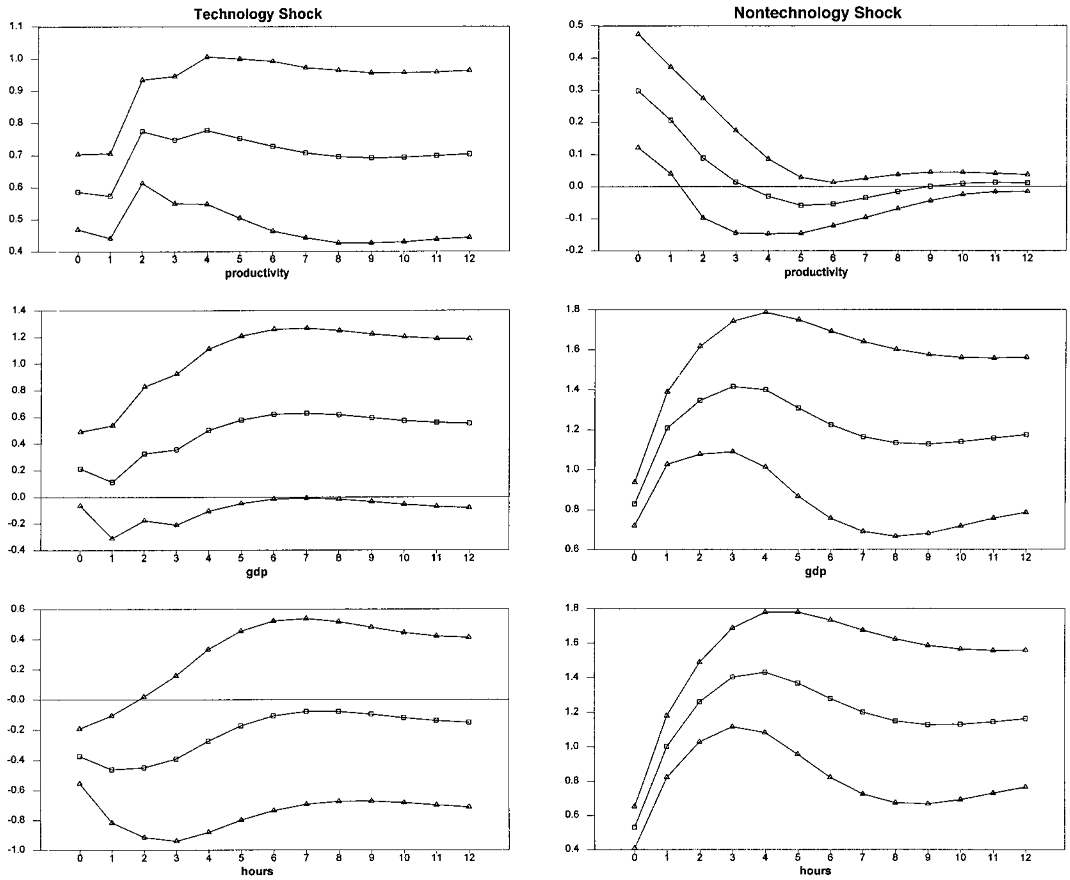

FIGURE 2. ESTIMATED IMPULSE RESPONSES FROM A BIVARIATE MODEL: U.S. DATA, FIRST-DIFFERENCED HOURS (POINT ESTIMATES AND ±2 STANDARD ERROR CONFIDENCE INTERVALS)

Table 2 displays the corresponding estimates of the productivity-labor input correlations conditional on each type of shock. As before, I report results using both Δn_t and $\hat{n}_t$ in the estimated VAR. The estimates largely confirm the results from the bivariate model: technology shocks induce a high, statistically significant negative correlation between productivity and hours (or employment), whereas the (composite) nontechnology component of the same variables shows a positive correlation (also significant in three out of the four specifications).

Figure 4 displays the responses of a number of variables to a technology shock. The pattern of responses of productivity, output, and employment is very similar to that obtained in the bivariate model: a positive technology shock leads to an immediate increase in productivity that is not matched by a proportional change in output (the latter's response building up more slowly over time), implying a transitory—though persistent—decline in hours. One small difference vis-à-vis Figures 2 and 3 can be detected, however: the initial negative effect on hours is now more than fully reversed over time, leading to a positive, though quantitatively small long-term effect.[23]

[23] That "reversal" does not occur, however, when employment is used as a labor-input measure (impulse responses not reported here).

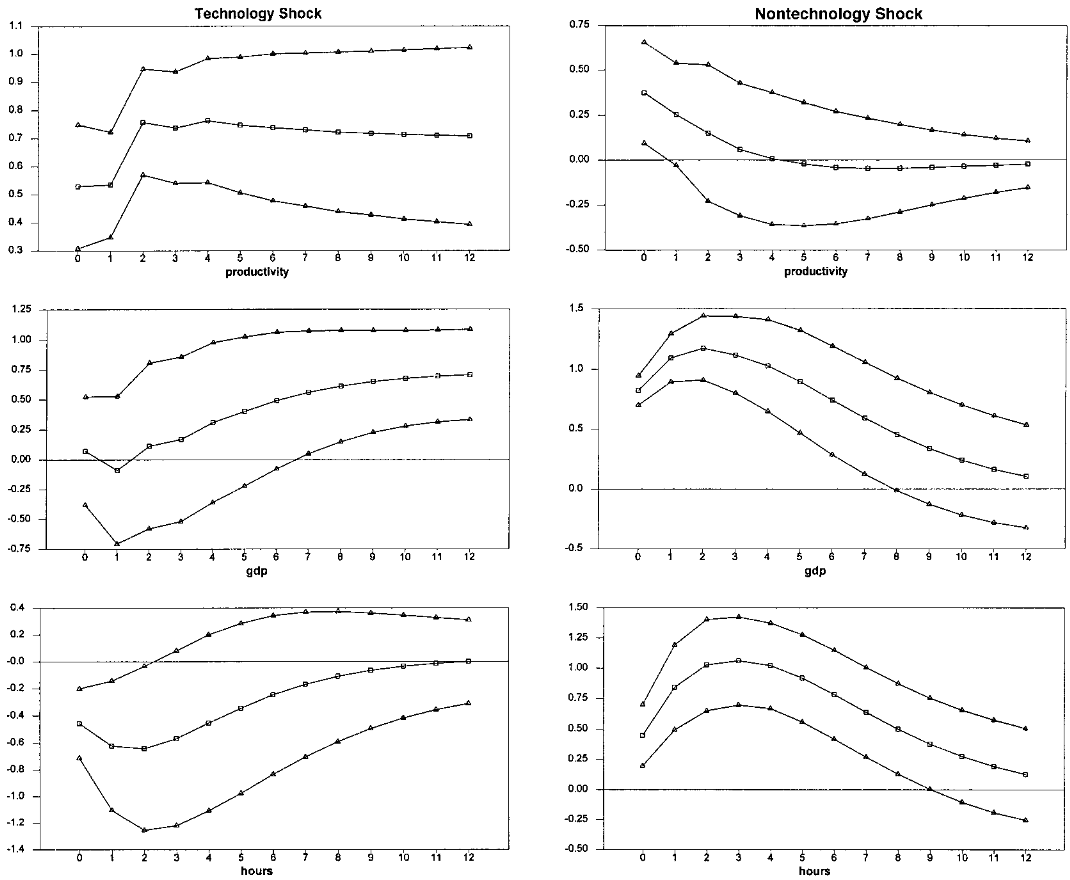

FIGURE 3. ESTIMATED IMPULSE RESPONSES FROM A BIVARIATE MODEL: U.S. DATA, DETRENDED HOURS (POINT ESTIMATES AND ±2 STANDARD ERROR CONFIDENCE INTERVALS)

Notice that the gradual response of output parallels the slow buildup of real balances over time. The response of the real rate to the improvement in technology is positive and persistent, in accordance with theory, given the higher returns to capital accumulation associated with that improvement. Most interestingly, the estimates point to a persistent negative impact on inflation (as opposed to a once-and-for-all drop in the price level). While the direction of the price change is reassuring (since it is consistent with the predictions of a broad class of models), the dynamic pattern seems consistent with the hypothesis of sluggish adjustment of prices over time, thus strengthening the ''new Keynesian'' interpretation suggested above.

C. *Evidence from Other Industrialized Economies*

This section reports estimates of productivity-employment correlations for the remaining G7 countries: Canada, the United Kingdom, Germany, France, Italy, and Japan.[24] For each country I estimate a bivariate VAR model for productivity and employment. The employment measure is the (log) employed civilian labor force, drawn from the OECD Quarterly

[24] Evidence for Spain using a related approach can be found in Galí (1996b). The intriguing results obtained in that project were the main impulse behind the present investigation.

TABLE 2—CONDITIONAL CORRELATION ESTIMATES: FIVE-VARIABLE MODEL

Conditional on:	Technology	Nontechnology
Panel A. Growth rates		
Hours	−0.75**	0.22**
	(0.04)	(0.09)
Employment	−0.82**	0.29**
	(0.08)	(0.08)
Panel B. Detrended		
Hours	−0.65**	−0.02
	(0.05)	(0.02)
Employment	−0.88**	0.26**
	(0.07)	(0.01)

Notes: Table 2 reports estimates of conditional correlations between the growth rates of productivity and labor input (hours or employment) in the United States Standard errors are shown in parentheses. Significance is indicated by one asterisk (10-percent level) or two asterisks (5-percent level). The conditional correlation estimates are based on the partially identified estimated five-variable VAR described in the text. The VAR is estimated using quarterly data for the period 1959:1–1994:4, and includes series for productivity, hours (or employment), real balances, real interest rates, and inflation. Panel A displays the results for the specification that includes labor-input growth. The results using detrended labor input are shown in Panel B. Data sources and definitions can be found in the text.

Labor Force statistics. The latter was subtracted from (log) GDP (drawn from the OECD Quarterly National Accounts) in order to construct the series for (log) labor productivity. All data are quarterly, and seasonally adjusted. Sample periods vary across countries, depending on data availability.[25]

Standard ADF unit root tests were applied to each series used.[26] With one exception, the tests did not reject at the 5-percent significance level a unit root in the (log) levels of employment and productivity. The exception was employment in France, for which the unit root null was rejected. That led me to estimate a VAR for $[\Delta x_t, \hat{n}_t]$ for France, and $[\Delta x_t, \Delta n_t]$ for the remaining countries. Identification and estimation of conditional correlations proceeds as in the bivariate U.S. model.

Table 3 reports, for each country, the estimated unconditional and conditional correlations of employment and productivity growth. The unconditional correlations are very small in absolute value (and largely insignificant), with the exception of Italy (−0.47). The average correlation is −0.11. Thus, and in accordance with the estimates based on U.S. data, there is no clear evidence of the large positive correlations between productivity and employment predicted by the basic, technology-driven RBC model.

Most interestingly, the estimated conditional correlations for most countries display the same sign pattern as in the United States. Thus, and with the exception of Japan, the estimates point to a *negative* correlation between the technology components of employment and productivity, with an average value of −0.56 (−0.75 if Japan is excluded). On the other hand, the nontechnology components show a *positive* correlation (again, with exception of Japan), which is significant in most cases, and has an average value of 0.26 (0.43 when Japan is excluded).[27]

Figure 5 displays, for each country, the estimated impulse responses of employment (solid line) and productivity (dashed line) to both types of shocks. With the exception of Japan, those responses show many of the qualitative features detected for the United States. In particular, the estimates point to a persistent decline in employment following a positive technology shock, as well as an increase in productivity accompanying an expansion driven by a nontechnology shock. Nevertheless, some differences are evident in a number of cases. Thus, technology shocks seem to have larger and more persistent effects on employment in Germany, the United Kingdom, and Italy. By way of contrast, in Canada the short-run negative impact of a positive technology shock on

[25] The sample periods are as follows: Canada (62:1–94:4), the United Kingdom (62:1–94:3), Germany (70:1–94:4), France (70:1–94:4), Italy (70:1–94:3), and Japan (62:1–94:4).

[26] A more detailed discussion of those tests can be found in Galí (1996a) or in the Appendix available upon request.

[27] Notice, however, that even though the pattern of signs of the conditional correlations is reversed for Japan the estimates are not statistically significant.

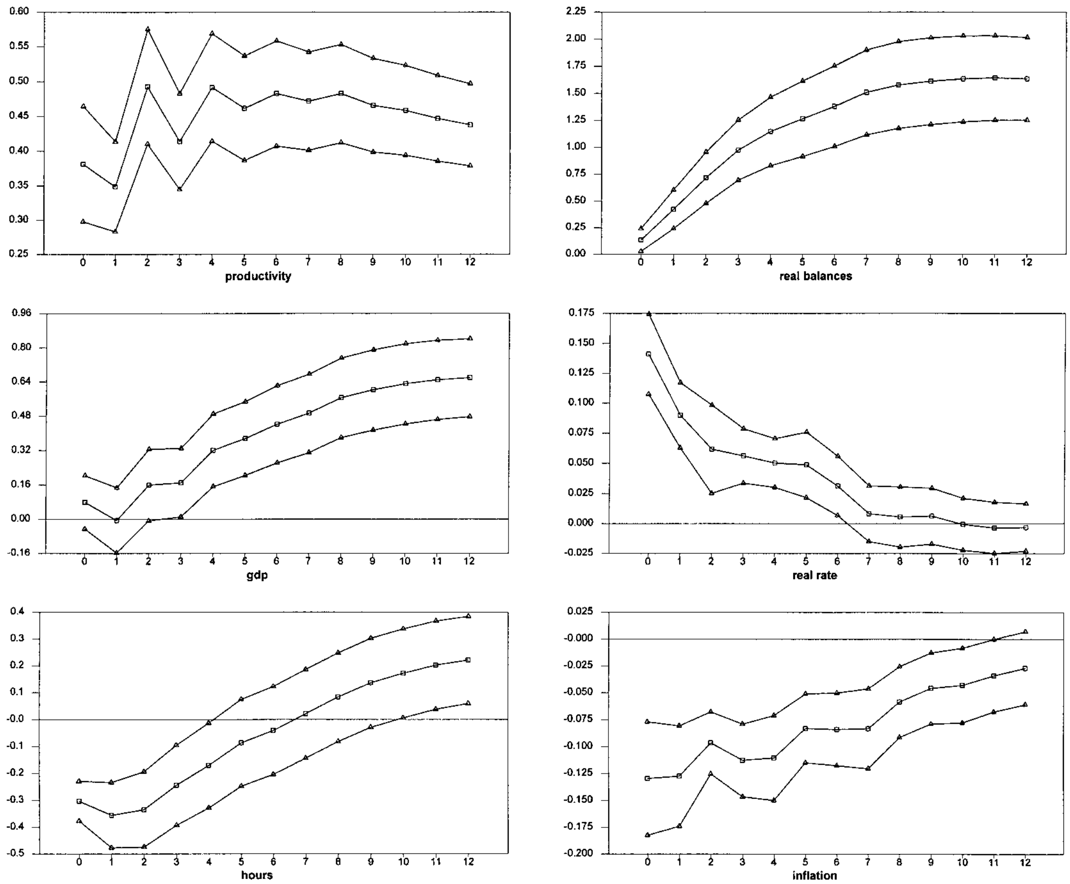

FIGURE 4. ESTIMATED IMPULSE RESPONSES FROM A FIVE-VARIABLE MODEL: U.S. DATA, FIRST-DIFFERENCED HOURS (POINT ESTIMATES AND ±2 STANDARD ERROR CONFIDENCE INTERVALS)

employment is fully reversed by the third quarter after the shock, and ends up having a strong positive effect asymptotically. How shall one interpret those differences? Given that none of the employment responses to the technology shock are statistically significant in the long run, one may be tempted to downplay the differences in point estimates.[28] Alternatively, one may want to interpret the persistence of those responses in some of the European countries as evidence of ''hysteresis'' in labor markets, along the lines suggested by Blanchard and Summers (1986). In a simple version of their model, wages are set in advance by unions/insiders so that, in expectation, next period's employment equals current employment. As a result, any shock that affects current employment will change the level of employment permanently. That mechanism could also underlie the permanent effects on employment resulting from nontechnology shocks that are observed in most countries, though more conventional explanations are available in that case, since those long-run effects may result from permanent shifts in the labor sup-

[28] A complete set of impulse responses with confidence intervals can be found in Galí (1996a).

TABLE 3—CORRELATION ESTIMATES: INTERNATIONAL EVIDENCE

	Unconditional	Conditional	
		Technology	Nontechnology
Canada	−0.12*	−0.59*	0.57*
	(0.08)	(0.32)	(0.32)
United Kingdom	−0.11	−0.91**	0.45**
	(0.13)	(0.16)	(0.14)
Germany	0.08	−0.55**	0.23**
	(0.10)	(0.28)	(0.09)
France	0.00	−0.81**	0.66**
	(0.11)	(0.27)	(0.29)
Italy	−0.47**	−0.93**	0.27
	(0.12)	(0.13)	(0.30)
Japan	−0.07	0.41	−0.60
	(0.08)	(0.47)	(0.42)
Average	−0.11	−0.56	0.26
Average (excluding Japan)	−0.12	−0.75	0.43

Notes: Table 3 reports estimates of unconditional and conditional correlations between the growth rates of productivity and employment for Canada (62:1–94:4), the United Kingdom (62:1–94:3), Germany (70:1–94:4), France (70:1–94:4), Italy (70:1–94:3), and Japan (62:1–94:4). Standard errors are shown in parentheses. Significance is indicated by one asterisk (10-percent level) or two asterisks (5-percent level). The conditional correlation estimates are computed using the procedure outlined in the text on the basis of an estimated bivariate VAR for productivity and employment growth (detrended employment for France). Data sources and exact definitions can be found in the text.

ply—whether exogenous (as in Shapiro and Watson, 1988), or induced by permanent fiscal policy changes (as in Baxter and King, 1983).

IV. Do Technology Shocks Generate Recognizable Business Cycles?

The bulk of the evidence in the previous section focused on the joint comovement—conditional and unconditional—of productivity and labor-input measures. In this section I turn briefly to the corresponding comovements between output and labor input.

A strong positive comovement of GDP and labor input is a central feature of business cycles in industrialized economies. Any theory of business cycles which failed to capture that feature would be viewed as empirically irrelevant and would arise little attention from the profession, so it is thus not surprising that a high positive correlation of output and hours lies among the key predictions of the basic RBC model driven by technology shocks. Yet, whether technology shocks in *actual* economies are responsible for the pattern of GDP and labor-input fluctuations associated with business cycles remains an open question, and one which should provide a critical test of the relevance of a research program that aims to interpret the bulk of aggregate fluctuations as resulting from those shocks. The empirical framework developed above can address that question by allowing one to decompose the historical time series for GDP and hours (or employment) into technology and nontechnology shocks.

The outcome of that exercise is displayed in Figure 6. In order to save space, I report only results for the United States, based on the bivariate VAR for $[\Delta x_t, \Delta n_t]'$. The figures display the estimated components of (log) GDP (solid line) and (log) hours (dashed line), after being detrended (*ex post*) using a HP filter ($\lambda = 1600$) in order to emphasize fluctuations at business-cycle frequencies. In addition, the figures highlight as vertical lines the nine

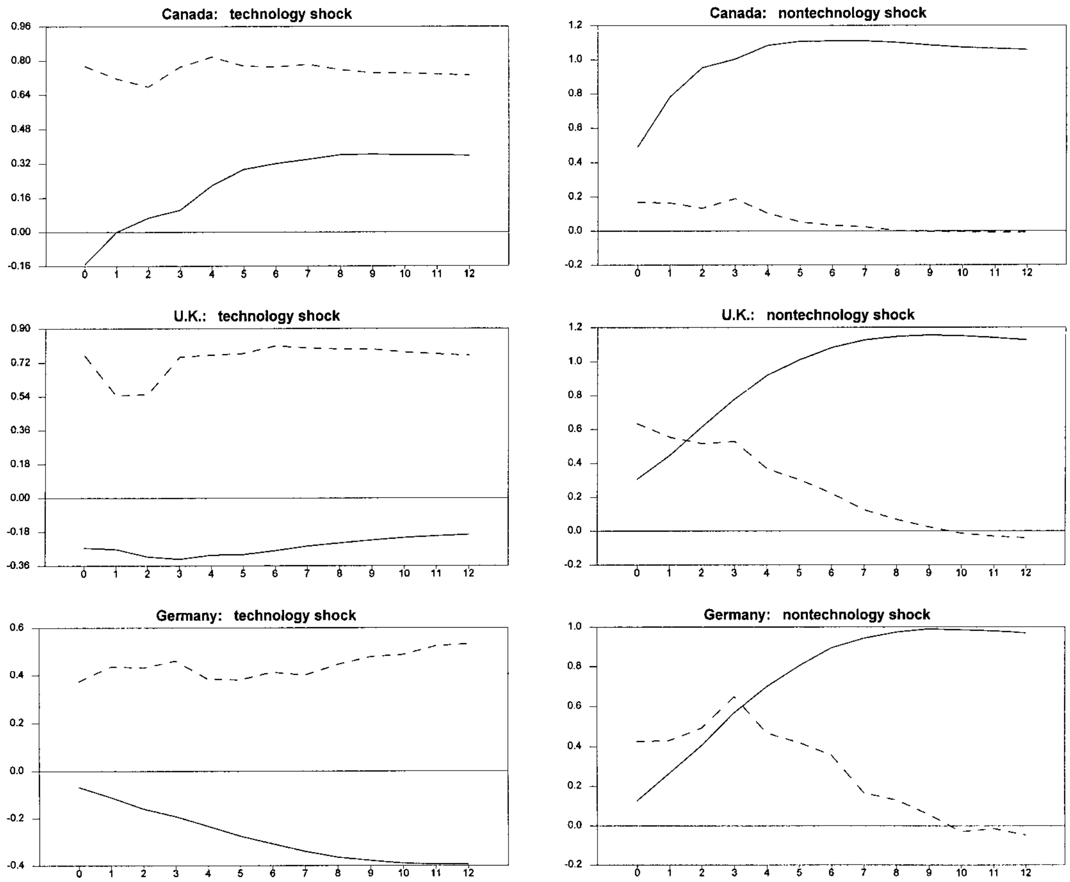

FIGURE 5. ESTIMATED IMPULSE RESPONSES OF EMPLOYMENT (SOLID LINE) AND PRODUCTIVITY (DASHED LINE) FOR OTHER INDUSTRIALIZED ECONOMIES

NBER-dated postwar recessions. The patterns that emerge are quite revealing in a number of ways.[29]

Consider the fluctuations that the empirical model identifies as having resulted from technology shocks (top chart). The patterns displayed by the two series hardly match any of the postwar cyclical episodes. That feature is particularly true in one dimension: the strong positive comovement of GDP and employment that is generally viewed as central characteristic of business cycles is conspicuously absent here; in fact, the estimated correlation between the two series is −0.02.

A look at the nontechnology components of the GDP and hours series (bottom chart) yields a completely different picture. First, such shocks are seen to have had a dominant role in postwar U.S. fluctuations. Second, the estimates point to an unambiguous pattern of positive comovements of GDP and hours associated with those nontechnology shocks, with an estimated correlation of 0.97. Third,

[29] Results for most other specifications and countries are qualitatively similar. In particular, an almost identical picture emerges when detrended hours are used in the VAR specification (see Appendix available upon request), which implies that the results reported here do not hinge on my allowing for permanent effects of nontechnology shocks on both output and hours.

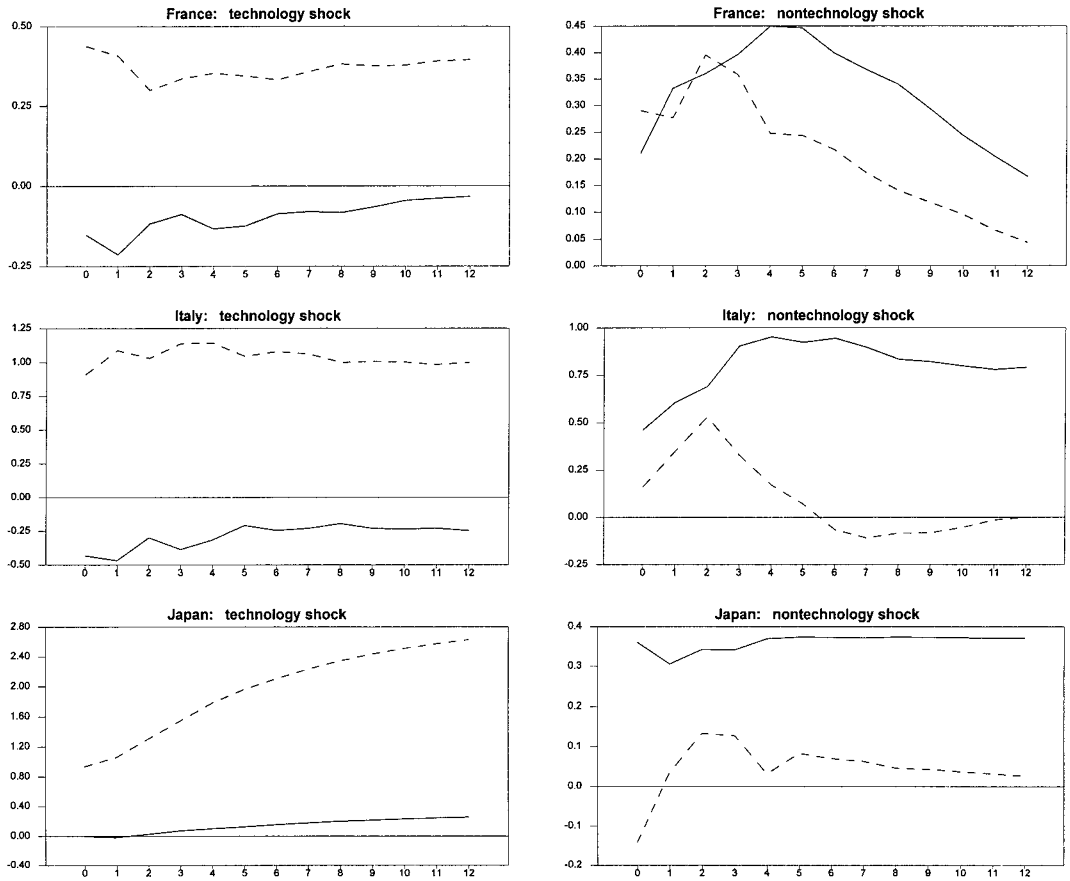

FIGURE 5. *Continued*

the resulting fluctuations account for the bulk of the decline in GDP and hours associated with postwar recessions.

V. Can the Evidence be Reconciled with the RBC Paradigm?

The above results strongly suggest that U.S. business cycles have been largely driven by disturbances that do *not* have permanent effects on labor productivity. To the extent that only technology shocks can account for the unit root in the latter variable, those results seem to provide a picture of U.S. business cycles that is in stark contrast with the one associated with RBC models. That conclusion may be strengthened by examining (and trying to refute) two arguments that have often been raised in order to reconcile the previous evidence with the RBC paradigm.

First, one might argue that the shocks that have been labeled all along as ''nontechnology'' shocks might also be capturing *transitory* shocks to technology, since the latter would generally have no permanent effect on the level of productivity. While there is nothing logically wrong with that interpretation, it can hardly provide any support for RBC models. For one thing, it is hard to understand how shocks to technology could be transitory, an observation which seems to conform with the failure to detect a significant transitory component in measures of total factor productivity (TFP) growth, which, to a first approximation,

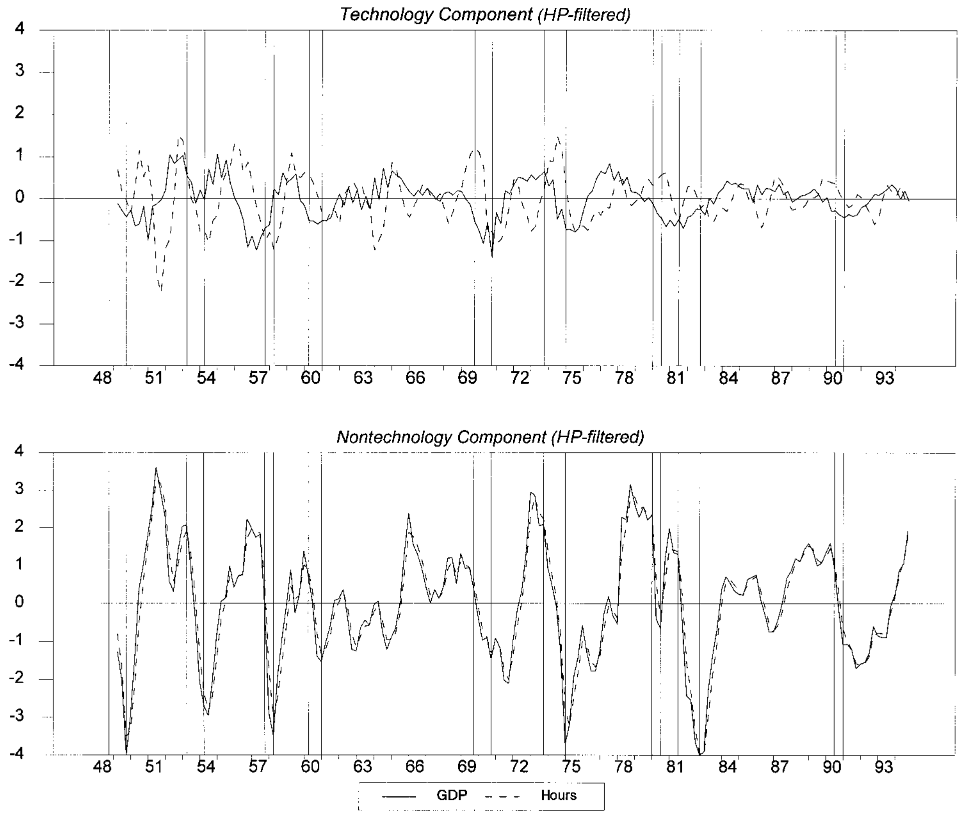

FIGURE 6. ESTIMATED TECHNOLOGY AND NONTECHNOLOGY COMPONENTS OF U.S. GDP AND HOURS

can be characterized as white noise.[30] Most importantly, such an interpretation leaves unanswered why *permanent* technology shocks would have the effects on the economy that are reflected in the estimated conditional correlations and impulse responses reported above.[31]

[30] This characterization seems to hold even when possible variations in inputs utilization rates are accounted for (see, e.g., Burnside and Eichenbaum, 1996).

[31] Nonstandard RBC models characterized by slow technology diffusion may generate a negative response of employment to a positive technology shock (see, e.g., Hairault et al., 1995) because of a dominant wealth effect (that makes people be willing to consume more leisure). That mechanism is, in my view, little plausible (in addition to being in conflict with the observed time-series properties of multifactor productivity).

Second, multisectoral RBC models with idiosyncratic technology shocks and lags in the reallocation of labor across sectors are likely to imply a short-term decline in aggregate employment in the wake of a positive technology shock in one sector (reflected in aggregate TFP), thus inducing a negative comovement consistent with the estimates above. In that context, however, the pattern of conditional correlations signs predicted by the RBC model should still be present in *sectoral data*, an implication that is in principle testable. Estimates of such correlations based on two-digit U.S. manufacturing data have recently been obtained by Michael T. Kiley (1997) using an identified VAR model for employment and productivity growth based on the one proposed and estimated in the present paper. Kiley's estimated correlations between the technology-driven components of those variables turn up negative for the vast majority of industries (15 out of 17) and quite high in absolute value (average = −0.58). The corresponding estimates for the nontechnology components are mostly positive (11 out of 17 industries), with an average value of 0.20. Kiley's sectoral results are thus clearly not supportive of a ''multisectoral RBC'' explanation for the aggregate evidence provided in this paper.

VI. Summary and Conclusion

In recent years, many macroeconomists have been attracted by the hypothesis that aggregate fluctuations can be explained, at least to a first approximation, as the economy's response to exogenous variations in technology. That view is often justified by the (largely recognized) ability of RBC models to generate *unconditional* moments for a number of macroeconomic variables that display patterns similar to their empirical counterparts.

The present paper has provided some evidence that questions the empirical merits of that class of models.[32] The paper builds on the observation of a near-zero unconditional correlation between productivity and employment, both in the United States and in many other industrialized economies. Proponents of RBC models have interpreted that evidence as reflecting the coexistence of technology shocks with other shocks. Yet, and to the extent that technology shocks are a significant source of fluctuations in those variables, we would expect RBC models to provide *at least* an accurate description of the economy's response to such shocks. For the majority of the G7 countries, however, the estimates of the effects of technology shocks yield a picture which is hard to reconcile with the predictions of those models: positive technology shocks lead to a decline in hours, and tend to generate a negative comovement between that variable and productivity. On the other hand, nontechnology shocks are shown to generate a positive comovement between hours and productivity, in contrast with the negative comovement predicted by RBC models with multiple shocks.

The results are, however, consistent with a class of models with imperfect competition, sticky prices, and variable effort. In those models—a stylized version of which has been presented in Section 1—the combination of price rigidities and demand constraints leads firms to contract employment in the face of an exogenous increase in multifactor productivity, whereas the presence of variable effort accounts for the rise in measured labor productivity in response to a demand-induced expansion. Needless to say, the nature of aggregate fluctuations and the potential role for policy associated with such an economy are very different from those identified with the RBC paradigm.

[32] Basu et al. (1997) obtain similar results using an unrelated approach: they look at the response of inputs to an innovation in a ''modified Solow residual'' series, where the modification attempts to correct for the bias associated with increasing returns, imperfect competition, variable utilization, and sectoral reallocations.

REFERENCES

Basu, Susanto. ''Procyclical Productivity: Increasing Returns or Cyclical Utilization?'' *Quarterly Journal of Economics*, August 1996, *111*(3), pp. 719–51.

Basu, Susanto; Fernald, John and Kimball, Miles. ''Are Technology Improvements Contractionary?'' Mimeo, University of Michigan, 1997.

Baxter, Marianne and King, Robert G. ''Fiscal Policy in General Equilibrium.'' *American Economic Review*, June 1993, *83*(3), pp. 315–34.

Bénassy, Jean-Pascal. ''Money and Wage Contracts in an Optimizing Model of the Business Cycle.'' *Journal of Monetary Economics*, April 1995, *35*(2), pp. 303–16.

Bencivenga, Valerie. ''An Econometric Study of Hours and Output Variation with Preference Shocks.'' *International Economic Review*, May 1992, *33*(2), pp. 449–71.

Bils, Mark and Cho, Jang-Ok. ''Cyclical Factor Utilization.'' *Journal of Monetary Economics*, April 1994, *33*(2), pp. 319–54.

Blanchard, Olivier J. ''A Traditional Interpretation of Macroeconomic Fluctuations.''

American Economic Review, December 1989, *79*(5), pp. 1146–64.

Blanchard, Olivier J. and Quah, Danny. ''The Dynamic Effects of Aggregate Demand and Supply Disturbances.'' *American Economic Review*, September 1989, *79*(4), pp. 654–73.

Blanchard, Olivier J.; Solow, Robert and Wilson, B. A. ''Productivity and Unemployment.'' Mimeo, Massachusetts Institute of Technology, 1995.

Blanchard, Olivier J. and Summers, Lawrence H. ''Hysteresis and the European Unemployment Problem,'' in Stanley Fischer, ed., *NBER macroeconomics annual 1986*. Cambridge, MA: MIT Press, 1986, pp. 15–78.

Burnside, Craig and Eichenbaum, Martin. ''Factor-Hoarding and the Propagation of Business-Cycle Shocks.'' *American Economic Review*, December 1996, *86*(5), pp. 1154–74.

Burnside, Craig; Eichenbaum, Martin and Rebelo, Sergio. ''Labor Hoarding and the Business Cycle.'' *Journal of Political Economy*, April 1993, *101*(2), pp. 245–73.

Calvo, Guillermo A. ''Staggered Prices in a Utility-Maximizing Framework.'' *Journal of Monetary Economics*, September 1983, *12*(3), pp. 383–98.

Cho, Jang-Ok and Cooley, Thomas F. ''The Business Cycle with Nominal Contracts.'' *Economic Theory*, June 1995, *6*(1), pp. 13–33.

Christiano, Lawrence J. and Eichenbaum, Martin. ''Current Real-Business-Cycle Theories and Aggregate Labor Market Fluctuations.'' *American Economic Review*, June 1992, *82*(3), pp. 430–50.

Cooley, Thomas F. and Dwyer, Mark. ''Business Cycle Analysis Without Much Theory: A Look At Structural VARs.'' Mimeo, University of Rochester, 1995.

Forni, Mario and Reichlin, Lucrezia. ''Let's Get Real: A Dynamic Factor Analytical Approach to Disaggregated Business Cycles.'' Centre for Economic Policy Research Discussion Paper No. 1244, September 1995.

Galí, Jordi. ''How Well Does the IS-LM Model Fit Postwar U.S. Data?'' *Quarterly Journal of Economics*, May 1992, *107*(2), pp. 709–38.

______. ''Government Size and Macroeconomic Stability.'' *European Economic Review*, January 1994, *38*(1), pp. 117–32.

______. ''Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?'' National Bureau of Economic Research (Cambridge, MA) Working Paper No. 5721, August 1996a.

______. ''Fluctuaciones y Persistencia del Empleo en España,'' in R. Marimon, ed., *La economía Española: Una visión diferente*. Barcelona: Antoni Bosch, 1996b, pp. 139–69.

Gamber, Edward N. and Joutz, Frederick L. ''The Dynamic Effects of Aggregate Demand and Supply Disturbances: Comment.'' *American Economic Review*, December 1993, *83*(5), pp. 1387–93.

Gordon, Robert J. ''Are Procyclical Productivity Fluctuations a Figment of Measurement Error?'' Mimeo, Northwestern University, 1990.

Greenwood, Jeremy; Hercowitz, Zvi and Krusell, Per. ''Long-Run Implications of Investment Specific Technological Change.'' *American Economic Review*, June 1997, *87*(3), pp. 342–62.

Hairault, Jean-Olivier; Langot, François and Portier, Franck. ''Time to Implement and Aggregate Fluctuations.'' Mimeo, CEPREMAP, Paris, January 1995.

Hairault, Jean-Olivier and Portier, Franck. ''Money, New-Keynesian Macroeconomics and the Business Cycle.'' *European Economic Review*, December 1993, *37*(8), pp. 1533–68.

Hansen, Gary D. and Wright, Randall. ''The Labor Market in Real Business Cycle Theory.'' *Federal Reserve Bank of Minneapolis Quarterly Review*, Spring 1992, *16*(2), pp. 2–12.

Kiley, Michael T. ''Labor Productivity in U.S. Manufacturing: Does Sectoral Comovement Reflect Technology Shocks.'' Mimeo, Federal Reserve Board, Washington, DC, 1997.

Kim, Jinill. ''Monetary Policy in a Stochastic Equilibrium Model with Real and Nominal Rigidities.'' Mimeo, Yale University, 1996.

King, Robert G. and Watson, Mark W. ''Money, Prices, Interest Rates and the Business Cycle.'' *Review of Economics and Statistics*, February 1996, *78*(1), pp. 35–53.

King, Robert G. and Wolman, Alexander L. ''Inflation Targeting in a St. Louis Model of the 21st Century.'' National Bureau of Economic Research (Cambridge, MA) Working Paper No. 5507, March 1996.

Kydland, Finn E. and Prescott, Edward C. ''Time to Build and Aggregate Fluctuations.'' *Econometrica*, November 1982, *50*(6), pp. 1345–70.

______. ''The Computational Experiment: An Econometric Tool.'' *Journal of Economic Perspectives*, Winter 1996, *10*(1), pp. 69–85.

Mishkin, Frederic S. ''Is the Fisher Effect for Real?'' *Journal of Monetary Economics*, November 1992, *30*(2), pp. 195–215.

Rotemberg, Julio J. ''Prices, Output, and Hours: An Empirical Analysis Based on a Sticky Price Model.'' *Journal of Monetary Economics*, June 1996, *37*(3), pp. 505–33.

Rotemberg, Julio J. and Woodford, Michael. ''Real-Business-Cycle Models and the Forecastable Movements in Output, Hours, and Consumption.'' *American Economic Review*, March 1996, *86*(1), pp. 71–89.

Sbordone, Argia M. ''Cyclical Productivity in a Model of Labor Hoarding.'' Mimeo, Princeton University, 1996.

Shapiro, Matthew D. ''Macroeconomic Implications of Variations in the Workweek of Capital.'' *Brookings Papers on Economic Activity*, 1996, (2), pp. 79–119.

Shapiro, Matthew D. and Watson, Mark W. ''Sources of Business Cycle Fluctuations,'' in Stanley Fischer, ed., *NBER macroeconomics annual 1988.* Cambridge, MA: MIT Press, 1988, pp. 111–48.

Sims, Christopher A. ''Models and Their Uses.'' *American Journal of Agricultural Economics*, 1989, *71*(2), pp. 489–94.

______. ''Macroeconomics and Methodology.'' *Journal of Economic Perspectives*, Winter 1996, *10*(1), pp. 105–20.

Singleton, Kenneth J. ''Specification and Estimation of Intertemporal Asset Pricing Models,'' in Benjamin M. Friedman and Frank H. Hahn, eds., *Handbook of monetary economics*, Vol. 1. Amsterdam: North-Holland, 1990, pp. 583–626.

Watson, Mark W. ''Measures of Fit for Calibrated Models.'' *Journal of Political Economy*, December 1993, *101*(6), pp. 1011–41.