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The Dynamic Effects of Neutral and Investment-Specific Technology Shocks

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The neoclassical growth model is used to identify the short-run effects of neutral technology shocks, which affect the production of all goods homogeneously, and investment-specific shocks, which affect only investment goods. The real equipment price, crucial for identifying the investment shocks, experiences an abrupt increase in its average rate of decline in 1982, so the analysis is based on a split sample. On the basis of the preferred specification, the two technology shocks account for 73 percent of hours' and 44 percent of output's business cycle variation before 1982, and 38 percent and 80 percent afterward. The shocks also account for more than 40 percent of hours' and 58 percent of output's forecast errors over a three- to eight-year horizon in both samples. The majority of these effects are driven by the investment shocks.

I. Introduction

This paper investigates how neutral and investment-specific technical change affect hours and output in the short run. Permanent neutral technology shocks can be identified if they are the only source of long-run changes in labor productivity. Galí (1999) and a growing literature use this assumption and find that technology shocks have only small

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short-run effects.[1] If true, this poses a significant challenge to the view that technology shocks are a major source of short-run fluctuations.[2] However, neutral shocks are not the only source of technical change. Greenwood, Hercowitz, and Krusell's (1997) finding that investment-specific technical change is a major source of economic growth suggests that it could be important for short-run fluctuations as well. This paper finds that technology shocks matter a lot when investment-specific technical change is introduced.

Introducing investment-specific technical change into a conventional RBC model motivates three long-run identifying restrictions. First, investment-specific change is an additional source of permanent shocks to labor productivity. Second, the model predicts that investment-specific change is the unique source of the secular trend in the real price of investment goods. These two assumptions exactly identify the short-run effects of both kinds of technical change. Third, the model predicts that investment-specific technical change raises labor productivity in the long run by a fixed proportion of its long-run impact on the investment good price. I show how this last prediction can be imposed as a long-run restriction and use it to refine my estimates.

The real equipment price is introduced to identify the investment-specific shocks. This price has been falling since the early 1950s and exhibits an abrupt increase in its average rate of decline in 1982. Given the other strong arguments to split the sample near that time—significant changes in monetary policy, aggregate volatility, and regulation—this abrupt change tips the weight of the evidence toward focusing on a split sample. Additionally justifying the split, the estimated dynamic responses of output and hours to technology shocks are very different before and after 1982. While different in character, the two samples' estimates both imply that technology shocks are quantitatively important for short-run fluctuations.

The paper considers three empirical specifications. In the preferred specification, the two shocks combined account for 73 percent and 38 percent of hours' and 44 percent and 80 percent of output's business cycle fluctuations before and after 1982. Over a horizon of three to

[1] Galí's fig. 6 (p. 268) is the clearest indication that technology shocks do not matter. Recent papers by Christiano, Eichenbaum, and Vigfussen (2004), Francis and Ramey (2005), and Galí and Rabanal (2005) confirm the result. Galí's paper builds on a long line of research into the effects of permanent technology shocks. The key early papers in this literature are Shapiro and Watson (1988), Blanchard and Quah (1989), and King et al. (1991).

[2] While the real business cycle (RBC) literature finds that transitory neutral shocks matter a lot, these results could be overstated. RBC studies traditionally assume a deterministic trend in technology and rely on Solow residuals to identify transitory shocks. Raw Solow residuals are an error-ridden measure of neutral technology over short horizons, so the shocks driving most RBC models could be implausibly large. See Basu, Fernald, and Kimball (2004) for a recent discussion of Solow residuals.

eight years the shocks also account for more than 40 percent and 58 percent of hours' and output's forecast errors in both samples. The investment-specific shocks account for the majority of these effects. The alternative specifications provide less clear-cut evidence on the role of the technology shocks. The two alternatives (drawn from the many that are considered in Fisher [2005]) show that technology shocks typically are found to have a prominent role in explaining hours and output fluctuations. But there are some exceptions, and each of the alternative specifications includes at least one case in which the results assign less importance to technology shocks than in the preferred specification. Evidence is presented suggesting that the identified shocks reflect technology and not shocks to other variables.

Section II uses a simple RBC model to derive the identifying assumptions at the heart of the analysis. Section III shows how these assumptions are used to identify the effects of technology shocks. After this, the data are discussed (Sec. IV), the main findings are presented (Sec. V), and the robustness of these findings is evaluated. Section VI summarizes and suggests directions for future research.

II. Theory

This section derives from a neoclassical growth model the long-run identifying assumptions exploited in the empirical analysis. The model is deliberately stripped down to make the discussion as transparent as possible. Some short-run implications of the model are also discussed, to motivate the analysis and to assess the plausibility of the empirical findings.

A. *The Model*

The model is adapted from the competitive equilibrium growth model of Greenwood, Hercowitz, and Krusell (1997). In this model the welfare theorems hold, so it is sufficient to explain the problem of the social planner. The planner chooses consumption, C_t, investment, X_t, hours worked, H_t, and next period's capital stock, K_{t+1}, to solve

$$\max \mathcal{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_t, H_t) \tag{1}$$

subject to

$$C_t + X_t \leq A_t K_t^{\alpha} H_t^{1-\alpha}, \quad \alpha \in (0, 1), \tag{2}$$

$$K_{t+1} \leq (1-\delta)K_t + V_t X_t, \quad K_0 \text{ given}, \delta \in (0, 1), \tag{3}$$

$$A_t = \exp(\gamma + \epsilon_{at})A_{t-1}, \quad \gamma \geq 0, \tag{4}$$

$$V_t = \exp(\nu + \epsilon_{vt})V_{t-1}, \quad \nu \geq 0, \tag{5}$$

and

$$[\epsilon_{at}, \epsilon_{vt}]' \sim N(0, \mathbf{D}), \quad \mathbf{D} \text{ diagonal.} \tag{6}$$

Here $\mathcal{E}_0$ is the expectations operator conditional on time $t = 0$ information; $U(\cdot, \cdot)$ is the utility function of the representative agent, assumed to be consistent with balanced growth; β is the planner's discount factor; A_t is the level of neutral technology; V_t is the level of investment-specific technology; and ϵ_{at} and ϵ_{vt} denote time t innovations to neutral and investment-specific technology.[3] For balanced growth to be feasible, it must be possible to express technical change as labor augmenting. So, with investment-specific technical change, balanced growth requires that the production function be Cobb-Douglas, as it is in (2).

The model simplifies the one in Greenwood, Hercowitz, and Krusell (1997) by incorporating one capital good instead of two. This difference is not crucial to the analysis. A second difference is that the exogenous technologies have stochastic instead of deterministic trends. This difference is substantial because it drives the permanent effects of technology. Permanent technology shocks are easily motivated. Many authors, including Galí (1999), view permanent technology shocks to be the natural way to model purely technological disturbances. Alvarez and Jermann (2005) present an empirical motivation. They find that it is impossible to resolve data on asset prices with economic theory without a permanent component to consumption. Nevertheless, a plausible interpretation of the neutral technology is that it represents many factors that influence production possibilities, such as taxes, regulations, and market structure. Disturbances to these variables might be transitory. Since the effects of transitory productivity shocks are not considered, the analysis should deliver a lower bound on the magnitude of the short-run effects of technology shocks broadly conceived.

[3] An equivalent way to state this model replaces the inequality in (2) with $(C_t/Z_t) + (\tilde{X}_t/\tilde{V}_t) \leq K_t^{\alpha}H_t^{1-\alpha}$, replaces the inequality in (3) with $K_{t+1} \leq (1-\delta)K_t + \tilde{X}_t$, and specifies Z_t and $\tilde{V}_t$ analogously to (4)–(6). This equivalence is seen by setting $A_t = Z_t$, $V_t = \tilde{V}_t/Z_t$, and $X_t = \tilde{X}_t/\tilde{V}_t$. The model also has an equivalent representation as a two-sector model, with identical factor shares in the consumption good and investment good sectors, and sector-specific technology terms given by A_t and A_tV_t or Z_t and $\tilde{V}_t$. It is natural to assume that innovations to the technology terms in the two sectors are correlated. The specification in the text permits this even under the assumption of a diagonal covariance matrix for the innovations. For the technologies to be correlated in the alternative specification, the innovation covariance matrix must be nondiagonal.

B. Long-Run Effects of Technology Shocks

Consider the model's predictions for the long-run or permanent impact of technical change on labor productivity, Y_t/H_t, and the consumption good price of an investment good, P_t. It is straightforward to confirm that along a balanced growth path the following variables are stationary:

$$\frac{Y_t}{Q_t},\ \frac{C_t}{Q_t},\ \frac{X_t}{Q_t},\ \frac{K_{t+1}}{Q_t V_t},\ \frac{Y_t/H_t}{Q_t},\ H_t, \tag{7}$$

where $Y_t = C_t + X_t$ and $Q_t = A_t^{1/(1-\alpha)} V_t^{\alpha/(1-\alpha)}$. Along a balanced growth path, the consumption value of output, consumption, investment, and labor productivity each grow, on average, at the rate $(\gamma + \alpha\nu)/(1-\alpha)$; the capital stock grows at the rate $(\gamma + \nu)/(1-\alpha)$; and per capita hours are stationary. From (7) it is immediate that positive innovations to both neutral and investment-specific technology increase labor productivity in the long run. That is, at any date t,

$$\lim_{j\to\infty} \frac{\partial \ln Y_{t+j}/H_{t+j}}{\partial \epsilon_{vt}} = \frac{\alpha}{1-\alpha} > 0,$$

$$\lim_{j\to\infty} \frac{\partial \ln Y_{t+j}/H_{t+j}}{\partial \epsilon_{at}} = \frac{1}{1-\alpha} > 0. \tag{8}$$

This implication is clearly different from the assumption implicit in Galí (1999) that only neutral technical change influences labor productivity in the long run.

An implication of (2) and (3) is that the number of consumption units that must be exchanged to acquire an efficiency unit of the investment good is $1/V_t$. Therefore, in the competitive equilibrium of this economy, the real price of an investment good is $P_t = 1/V_t$. It follows trivially that only investment-specific technology shocks have permanent effects on the real investment good price. Neutral technical change has no impact on the marginal rate of transformation between consumption goods and investment goods and therefore on the real price of investment. At any date t,

$$\lim_{j\to\infty} \frac{\partial \ln P_{t+j}}{\partial \epsilon_{vt}} = -1 < 0, \quad \lim_{j\to\infty} \frac{\partial \ln P_{t+j}}{\partial \epsilon_{at}} = 0. \tag{9}$$

The model can be extended to include additional exogenous shocks. As long as these shocks are transitory, the model will continue to satisfy (7) and $P_t = 1/V_t$. This leads to another useful implication of the model:

$$\lim_{j\to\infty} \frac{\partial \ln Y_{t+j}/H_{t+j}}{\partial \epsilon_{xt}} = 0, \quad \lim_{j\to\infty} \frac{\partial \ln P_{t+j}}{\partial \epsilon_{xt}} = 0, \tag{10}$$

for all other transitory shocks ϵ_{xt}.

The final implication of the model exploited in the empirical analysis is that innovations to the investment-specific technology have a predictable long-run impact on labor productivity relative to the real investment good price. Specifically, from (8) and (9), it follows that a unit innovation to the investment-specific technology lowers the real price of investment goods by a unit and raises labor productivity by $\alpha/(1-\alpha)$:

$$\frac{1-\alpha}{\alpha}\lim_{j\to\infty}\frac{\partial \ln Y_{t+j}/H_{t+j}}{\partial \epsilon_{vt}} + \lim_{j\to\infty}\frac{\partial \ln P_{t+j}}{\partial \epsilon_{vt}} = 0. \tag{11}$$

The specific constant of proportionality in (11) depends on the model having one sector and one capital good. However, versions of (11) with different constants of proportionality continue to hold for models with multiple capital goods and multiple sectors (see Greenwood, Hercowitz, and Krusell 1997).

Implications (8)–(11) are quite general since they follow from the assumptions on preferences and technology necessary for balanced growth. So models with additional endogenous variables and propagation mechanisms, including models with nominal rigidities, are consistent with (8)–(11). As an example, consider the model's implication that the real investment price is determined exogenously by investment-specific technical change. A more realistic model would have curvature in the transformation frontier for producing investment and consumption goods, for example, the two-sector model studied by Boldrin, Christiano, and Fisher (2001). In such a model, the real investment good price is endogenous over short horizons. Yet, as long as the model is consistent with balanced growth and is subject to neutral and investment-specific technical change, and technical innovations have a permanent impact on the production possibilities frontier, it will continue to satisfy (8)–(11).

C. *Short-Run Effects of Technology Shocks*

This subsection discusses the short-run responses of endogenous variables to technology shocks in the model. These responses are *not* used to identify the effects of technology shocks, but they help to motivate the study of investment-specific shocks and assess the plausibility of the responses identified from the data. Figure 1 plots the responses of various model variables to 1 percent positive innovations in the neutral technology (solid lines) and the investment-specific technology. The figure shows the responses of the real investment price, labor productivity, per capita hours, output, investment in units of capital (V_tX_t), and

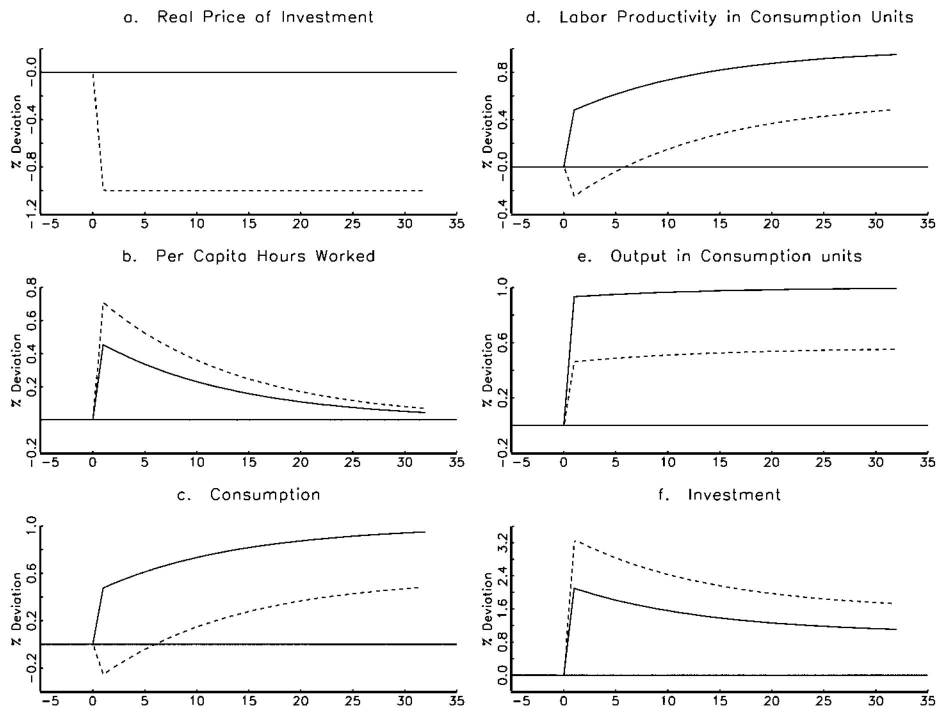

FIG. 1.—Theoretical responses to investment-specific and neutral technology shocks. Solid lines denote responses to a neutral shock and dashed lines responses to an investment-specific shock.

consumption. Output and productivity are measured in consumption units. These plots are based on the following assumptions: $U(C_t, H_t) = \ln(C_t) - H_t$, $\alpha = 1/3$, $\delta = 0.025$, $\beta = 0.99$, $\nu = -0.0046$, and $\gamma = 0.0026$. The technology growth parameters ν and γ are consistent with the data used in the empirical analysis. The other parameter values and the functional form for the utility function are consistent with much of the RBC literature.

The responses of the investment price follow directly from the fact that the price equals the inverse of the investment-specific technology, V_t. To understand the other responses it is helpful to focus on hours worked. These responses are both positive, and the investment-specific shock (I-shock) has a larger effect. The response of hours to a neutral technology shock (N-shock) is due to the intertemporal substitution of current leisure and consumption for future consumption. The household is willing to do this because of the high returns to working and saving. These intertemporal substitution effects operate after an I-shock as well, but they are amplified, as is the response of hours worked.[4] This amplification occurs because the shock directly affects only the production of investment goods. Consequently, current consumption is even more expensive relative to future consumption, compared to the N-shock case. This difference drives the stronger response of investment to an I-shock and the fact that the consumption response to an I-shock always lies below its N-shock counterpart. The response of productivity to an N-shock is well understood. With an I-shock, productivity initially drops before slowly rising to its long-run level. This response arises from the immediate positive response of hours, the slow response of capital, and the fact that the shock does not directly affect output's consumption value.

The hours and productivity responses suggest why estimates of the effects of technology shocks assuming that only neutral shocks have long-run productivity effects might be misleading. According to the aggregation theorem in Blanchard and Quah (1989, 670), the effects of technology shocks derived from vector autoregressions (VARs) in productivity and hours are robust to the presence of additional technology shocks that affect productivity in the long run *if and only if* the responses to the individual technology shocks are sufficiently similar. The specific condition is that the ratio of the hours and productivity responses must be invariant to the source of the technology shock. If this condition holds, then the estimated response of hours to a one-standard-deviation productivity shock is the sum of the hours responses

[4] See Greenwood, Hercowitz, and Huffman (1988) for a model without intertemporal substitution effects on labor supply in which hours respond positively to an investment-specific shock.

to a one-standard-deviation shock to each of the technology shocks. Figure 1 shows that Blanchard and Quah's necessary and sufficient condition is not satisfied here. With a neutral shock, productivity rises faster than hours in the period of the shock and thereafter. With an investment-specific shock, hours initially rise faster than productivity, before productivity catches up and overtakes it.[5]

Taken together, the responses in figure 1 indicate that the simple neoclassical model is qualitatively consistent with many characteristics of the U.S. business cycle, such as the procyclicality of hours, consumption, and investment.[6] Consequently, the two technology shocks could, in principle, account for a large or a small fraction of short-run fluctuations, and I-shocks could be more, less, or equally as important as N-shocks. The actual effects of the technology shocks predicted by the model depend on the magnitudes of the two shocks.

The RBC literature studies investment-specific technical change and finds that it has large short-run effects. The earliest paper is Greenwood, Hercowitz, and Huffman (1988). Other papers include Fisher (1997), Campbell (1998), Christiano and Fisher (1998), and Greenwood, Hercowitz, and Krusell (2000). Greenwood, Hercowitz, and Krusell take the investment technology (3) literally and identify all movements in the investment price with technology. In general, the effects of technology shocks derived from studies like these depend on the specifics of the propagation mechanism embedded in the model under consideration. The econometric approach described in the next section has two advantages: it allows other variables and shocks to influence the investment price and it takes a much weaker stand on the nature of the propagation mechanism.

III. Econometric Strategy

The econometric strategy is based on three assumptions, which summarize the long-run implications of models for which (8)–(11) hold. These are summarized as follows.

Assumption 1. Only I-shocks affect the investment price in the long run.

[5] For the calibrated model underlying fig. 1, it is straightforward to compute the probability limit of the response of hours one would obtain from a VAR in productivity and hours under the (false) assumption that neutral shocks are the only shocks to affect productivity in the long run. The resulting response lies substantially below the true average response of hours to neutral and investment-specific shocks. This confirms the theoretical possibility that previous estimates understate the contribution of technology shocks to short-run fluctuations.

[6] The response of consumption in the first few periods after an I-shock can be made positive by the addition of habit persistence to the model.

Assumption 2. Only N- and I-shocks affect labor productivity in the long run.

Assumption 3. I-shocks that lower (raise) the investment good price by an amount x raise (lower) labor productivity in a known fixed proportion to x.

This section describes how to use these assumptions to identify variables' dynamic responses to exogenous neutral and investment-specific technology shocks.[7]

The linear approximation to the equilibrium of the economic model has a moving average representation

$$\boldsymbol{y}_t = \boldsymbol{\Phi}(L)\boldsymbol{\epsilon}_t, \tag{12}$$

where $\boldsymbol{y}_t$ is an $n \times 1$ vector of states and controls; $\boldsymbol{\epsilon}_t$ is a vector of exogenous shocks with ϵ_{vt} and ϵ_{at} as the first two elements; $\mathcal{E}\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t' = \boldsymbol{\Omega}$, where $\boldsymbol{\Omega}$ is a diagonal matrix; and $\boldsymbol{\Phi}(L)$ is a matrix of polynomials in the lag operator L. The elements of $\boldsymbol{y}_t$ are $[\Delta p_t, \Delta a_t, h_t, \boldsymbol{q}_t]'$, where p_t is the log of the investment price, a_t is the log of labor productivity, h_t is the log of per capita hours worked, $\boldsymbol{q}_t$ is a vector of other endogenous variables in the model, and $\Delta \equiv 1 - L$.

Assume that $\boldsymbol{\Phi}(L)$ is invertible and that its inverse is well approximated by a finite-order lag polynomial.[8] The (approximate) VAR representation of (12) can be written

$$\mathbf{A}\boldsymbol{y}_t = \boldsymbol{\Gamma}(L)\boldsymbol{y}_{t-1} + \boldsymbol{\epsilon}_t, \tag{13}$$

where $\boldsymbol{\Gamma}(L)$ is an $N-1$–order matrix lag polynomial and $\mathbf{A}$ is a matrix conformable with $\boldsymbol{y}_t$, normalized to have ones along the diagonal. With estimates of $\mathbf{A}$ and $\boldsymbol{\Gamma}(L)$, (13) is simulated to derive the impulse response functions of interest. Equation (13) is estimated using a series of instrumental variables regressions.

The first equation of (13) is

$$\Delta p_t = \Gamma_{pp}(L)\Delta p_{t-1} + \Gamma_{pa}(L)\Delta a_t + \Gamma_{ph}(L)h_t + \boldsymbol{\Gamma}_{pq}(L)\boldsymbol{q}_t + \epsilon_{vt}, \tag{14}$$

where the $\Gamma_{xy}(L)$'s here and below are the relevant lag polynomials. According to (14), the contemporaneous effects of all non-ϵ_{vt} shocks influence Δp_t through Δa_t, h_t, and $\boldsymbol{q}_t$. Assumption 1 implies that the long-run multipliers from these variables to the real price are zero. Imposing this restriction is the same as imposing a unit root in each of the lag

[7] The estimation strategy borrows from Shapiro and Watson (1988). See Basu and Fernald (2002) for a different strategy for identifying technology shocks that does not rely on long-run restrictions. Basu et al. (2005) show how to extend this methodology to identify sector-specific technology shocks.

[8] Fernandez-Villaverde, Rubio-Ramirez, and Sargent (2004) demonstrate that a calibrated version of the model described in the previous section is indeed invertible. They also show that the infinite-order VAR representation of the two-variable system with Δp_t and Δa_t is almost identical to the representation with just one lag.

polynomials associated with Δa_t, h_t, and $\boldsymbol{q}_t$. That is, each $\Gamma_{pj}(L)$, $j = a$, h, $\boldsymbol{q}$, can be written $\Gamma_{pj}(L) = \tilde{\Gamma}_{pj}(L)(1-L)$ and $\boldsymbol{\Gamma}_{pq}(L) = \tilde{\boldsymbol{\Gamma}}_{pq}(L)(1-L)$. It follows that (14) becomes

$$\Delta p_t = \Gamma_{pp}(L)\Delta p_{t-1} + \tilde{\Gamma}_{pa}(L)\Delta^2 a_t + \tilde{\Gamma}_{ph}(L)\Delta h_t + \tilde{\boldsymbol{\Gamma}}_{pq}(L)\Delta \boldsymbol{q}_t + \epsilon_{vt}. \quad (15)$$

Innovations to the real investment price affect the contemporaneous values of Δa_t, h_t, and $\boldsymbol{q}_t$, so (15) cannot be estimated by ordinary least squares. However, assuming that ϵ_{vt} is exogenous means that this shock is orthogonal to all variables dated $t-1$ and earlier. So (15) is estimated by instrumental variables, using N lags of $\boldsymbol{y}_t$ as instruments. The coefficients of the first equation of (13) are found by unraveling the resulting regression coefficients. The residuals from (15) are the estimates of ϵ_{vt} and $\hat{\epsilon}_{vt}$.

By a similar argument used with the first equation, assumption 2 implies that the long-run multipliers from h_t and $\boldsymbol{q}_t$ to Δa_t are zero in the second equation of (13). It follows that this second equation can be written

$$\Delta a_t = \Gamma_{ap}(L)\Delta p_t + \Gamma_{aa}(L)\Delta a_{t-1} + \tilde{\Gamma}_{ah}(L)\Delta h_t + \tilde{\boldsymbol{\Gamma}}_{aq}(L)\Delta \boldsymbol{q}_t + \epsilon_{at}, \quad (16)$$

where the $\tilde{\Gamma}_{aj}(L)$, $j = h$, $\boldsymbol{q}$, are defined in the same way as the similar terms in (15). As before, this equation is estimated by instrumental variables, and the resulting coefficient estimates are used to assign values to the second row of coefficients in (13). The instruments are $\hat{\epsilon}_{vt}$ and N lags of $\boldsymbol{y}_t$. The residuals from (16), $\hat{\epsilon}_{at}$, are the estimates of ϵ_{at}. Including $\hat{\epsilon}_{vt}$ as an instrument ensures that $\hat{\epsilon}_{at}$ is orthogonal to the investment-specific shock within the sample period. These steps toward estimating the effects of the neutral shock differ from Galí's (1999) method because the real price is included in (16) and the residuals from (14) are included as an instrument.

The first two equations of (13) are exactly identified. It is straightforward to show that there exists a family of parameterizations of the remaining rows of (13) in which the estimated responses to ϵ_{at} and ϵ_{vt} are invariant. An element of this family is chosen by estimating the remaining equations of (13) sequentially by instrumental variables, using the residuals from the previously estimated equations and N lags of $\boldsymbol{y}_t$ as instruments. Following this procedure does not impose any restrictions on the impulse responses of interest.

The discussion so far makes it clear that assumption 3 is not necessary to identify variables' responses to the two technology shocks. There are two reasons to impose assumption 3. First, it is a way to test the model. The identification strategy's viability is testable using auxiliary information about the share of capital in production. Second, imposing an overidentifying restriction improves the precision of the estimates. Appendix A shows that, under assumptions 1 and 2, assumption 3 implies a simple linear restriction on the coefficients of the second equation of (13). To state this restriction, define $\mathbf{C}(L) = \mathbf{A} - \mathbf{\Gamma}(L)L$ and let the ijth element of $\mathbf{C}(1)$ be denoted c_{ij}. In the context of the model described in Section II, the restriction is

$$\frac{1-\alpha}{\alpha}c_{21} - c_{22} = 0. \tag{17}$$

From (11),

$$c_{21} = \lim_{j\to\infty}\frac{\partial \ln (Y_{t+j}/H_{t+j})}{\partial \epsilon_{vt}}$$

and

$$c_{22} = -\lim_{j\to\infty}\frac{\partial \ln P_{t+j}}{\partial \epsilon_{vt}}.$$

In practice, (17) is rarely rejected at conventional significance levels. For the specifications described in this paper, the marginal significance levels range from 28 percent to 87 percent. So all the findings involve estimates of (13) in which (17) is imposed.

It is important to address the statistical properties of this methodology. Cooley and Dwyer (1998), Erceg, Guerriera, and Gust (2004), and most recently Christiano et al. (2006) discuss situations in which long-run restrictions might yield misleading results. Obviously, if assumptions 1–3 do not hold, then the analysis is invalid. Less obvious is how well the methodology works in small samples when the assumptions do hold. Christiano et al. document the small-sample properties of a business cycle model with a neutral technology shock. They find that for empirically plausible parameters there is hardly any small-sample bias, and standard errors accurately reflect the true uncertainty in the estimates. The previous literature considers only exactly identified models. Overidentifying restriction (17) should improve the methodology's small-sample properties.

IV. Data

This section discusses the investment price data and their connection with measures of the user cost of capital, and it describes the remaining variables included in the empirical analysis. Appendix B contains additional information on the data.

A. *The Real Price of Investment*

Clearly the real investment price is a crucial input to the analysis. This price is measured as an investment deflator divided by a consumption deflator. The consumption deflator corresponds to nondurable and service consumption, the service flow from consumer durables, and government consumption. It is derived directly from the National Income and Product Accounts (NIPA).

Investment deflators pose more difficulties. Greenwood, Hercowitz, and Krusell (1997) emphasize the lack of quality adjustment in the NIPA investment deflators. Their analysis is based on Gordon's (1989) producer durable equipment deflator, which incorporates a wide range of quality adjustments. Moulton (2001) reveals that the NIPAs currently incorporate hedonic methods to quality-adjust computers, semiconductors, software, and digital telephone switching equipment, but other types of equipment are not adjusted. Consequently, the NIPA equipment deflator could still be biased, especially in the years prior to 1982, when the share of investment in quality-adjusted equipment is small. Residential structures investment is extensively quality-adjusted, but nonresidential structures investment is not.

Greenwood, Hercowitz, and Krusell (1997) show with an extended version of Section II's model that, because of the large decline in the real equipment price based on Gordon's deflator, investment-specific technical change accounts for 58 percent of output growth between 1954 and 1990. Greenwood et al. use a rough bias adjustment to extend Gordon's original sample, whereas Cummins and Violante (2002) systematically update the Gordon series. For component deflators not already quality-adjusted in the NIPAs, they use Gordon's deflators to estimate econometric models of the bias adjustment. Combining the estimated deflators with the NIPA's quality-adjusted deflators, they construct a new quality-adjusted equipment deflator extending to 2000 and confirm the Greenwood et al. findings.

This paper considers four investment deflators. The first measure is "equipment," which is just the Gordon-Cummins-Violante (GCV) equipment deflator.[9] The second is "total investment," a broader measure constructed with the GCV deflator and the NIPA deflators for nonresidential and residential structures, consumer durables, and government investment. This deflator corresponds to the measure of investment often used in RBC studies. The two other deflators used in the analysis are the NIPA counterparts to these two deflators.

[9] The econometric analysis is based on quarterly data. Since the GCV series is an annual series, it is interpolated. Appendix B describes in detail how this is done. Briefly, the procedure maintains the year-to-year trends in the GCV series and uses the corresponding NIPA deflator to derive within-year fluctuations.

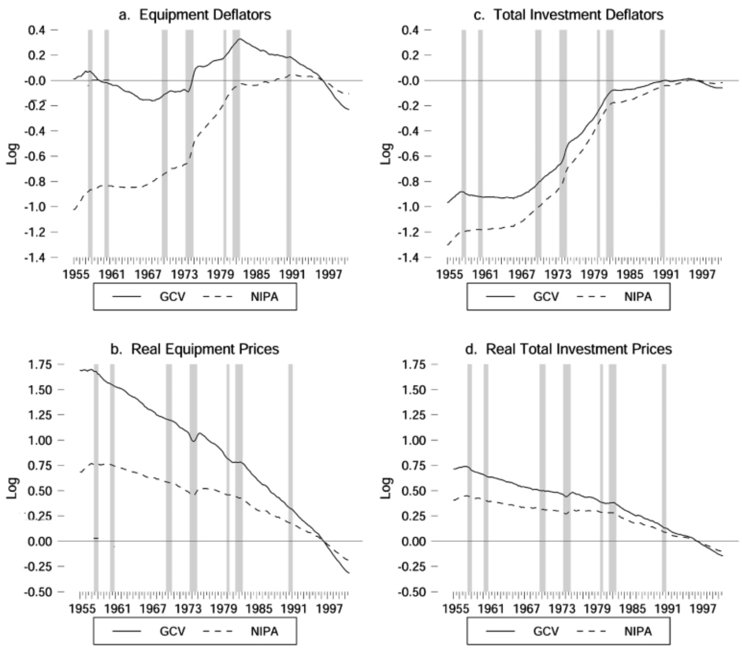

FIG. 2.—Two measures of nominal and real investment prices

Figure 2 displays, in logs, the two GCV and NIPA investment deflators and the associated real investment prices for the sample period 1955:I–2000:IV.[10] First, note that the quality bias in the NIPA deflators (dashed lines) is apparently quite large. Second, there is a 200 percent drop in the GCV price. Third, changes in the equipment price in the 1973–74 period are influenced by the Nixon wage and price controls (see Cummins and Violante 2002). Since this is a transitory phenomenon, it should not affect the estimation of the technology shocks. Fourth, there is a kink in the plot of the GCV real equipment price because the mean rate of decline in the price rises from 3.4 percent a year before 1982 to 5.8 percent after. Fifth, the real total investment prices decline by much less than the equipment prices but still have secular trends and kinks near 1982. The weaker trends in this price might be due to slower rates of quality change in nonequipment investment, or the deflators for nonequipment investment goods might embody less quality adjust-

[10] There are three reasons to exclude data before 1955. First, the RBC literature often focuses on the post–Korean War era (see Prescott 1986). Second, the interpolations of the equipment deflator before 1955 are questionable because the quality bias in the NIPA data appears to be quite severe in this period. Third, estimates of neutral technology shocks are sensitive to including variables associated with monetary policy. This suggests that the sample should begin after the Treasury Accord of 1951.

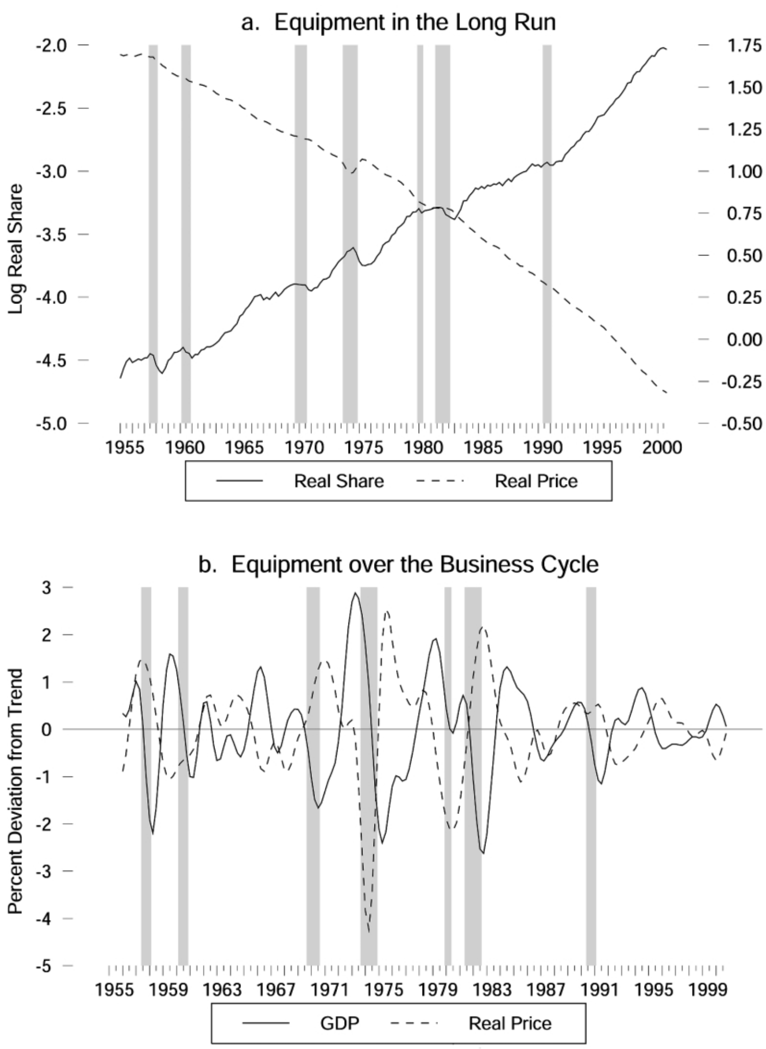

FIG. 3.—Real equipment prices in the long run and over the business cycle

ment. For example, Gort, Greenwood, and Rupert (1999) estimate significant quality bias in the NIPA deflators for nonresidential structures.

Figure 3 suggests why the investment price could be important for understanding macroeconomic dynamics (similar plots appear in Greenwood, Hercowitz, and Krusell [1997, 2000]). Figure 3*a* reproduces the GCV real equipment price from figure 2 along with the log ratio of the quantity of equipment in units of capital to gross domestic product in consumption units. This plot shows that the real price decline coincides with a large increase in the relative quantity of investment goods produced, illustrating the importance of investment-specific technical change for capital accumulation and growth.[11] Figure 3*b* displays the business cycle components of the GCV equipment price and GDP.[12] This shows a clear negative relationship between the equipment price and output, strongly suggesting a role for investment cost shocks in aggregate fluctuations. The unconditional correlation is -0.54 and is highly significant. This correlation is even stronger when the NIPA equipment price is used and is somewhat weaker, but still significantly negative, when total investment prices are used.

While figure 3 suggests that investment-specific technology shocks could play a key role in short-run fluctuations, the short-run correlations might be driven at least partly by factors other than technical change, such as time-varying markups. As Ramey (1996) argues, markups might play a role in the long-run dynamics as well. The long-run identifying restrictions extract just the technology-driven component from the short-run movements in the investment price. This strategy is robust to trends in markups if there is no tendency for markups to decline more in producing investment goods than in producing consumption goods.

B. *The Investment Price and User Cost*

Investment prices are also highly negatively correlated with investment expenditures at business cycle frequencies. This might seem surprising in light of the weak correlation between investment and measures of its user cost typically found in the literature. The user cost of equipment is the investment price multiplied by two terms. These terms are a tax adjustment and a term equal to the sum of interest, depreciation, and the expected capital loss. The weak correlations in the literature arise from focusing on growth rates. For example, Hassett and Hubbard (2002) find that the correlation between four-quarter changes in equipment investment and its user cost is -0.11. If instead one examines correlations at business cycle frequencies, the correlations are similar to the corresponding ones based on investment prices.

Table 1 suggests why focusing on growth rate correlations and making inferences might be misleading. This shows correlations of two types of equipment with measures of the investment price and different mea-

[11] The model predicts that the nominal share of investment is stationary. Equipment is not consistent with this, but total investment is.

[12] Business cycle components are derived using Christiano and Fitzgerald's (2003) implementation of the band-pass filter, excluding frequencies higher than one and a half years and lower than eight years.

TABLE 1
CORRELATIONS WITH EQUIPMENT INVESTMENT

Variable	1964:I–2004:IV	1964:I–1979:II	1982:III–2004:IV
	A. Non-High-Tech Equipment		
P	−.74	−.84	−.57
Δuc	−.11	−.14	−.02
uc	−.55	−.54	−.58
uc*	−.76	−.90	−.62
	B. High-Tech Equipment		
P	−.60	−.68	−.49
Δuc	.07	.12	−.08
uc	−.12	−.14	.01
uc*	−.52	−.42	−.64

NOTE.—Unless a Δ precedes a variable, the correlation is based on business cycle frequencies; otherwise it is based on growth rates. In the non-high-tech case, the expected capital gain is based on a first-order autoregression in growth rates of the price (higher-order coefficients are not significant). In the high-tech case, expectations are based on an autoregression with four lags. The start of the sample is governed by availability of the user cost data from the Federal Reserve Board.

* The depreciation and tax variables have been replaced by their means.

sures of user cost. The user cost data for interest, depreciation, and taxes are taken from the Federal Reserve Board's FRB/US econometric model. In the table, high-tech equipment corresponds to the NIPA's hedonically adjusted equipment prices described above. The prices are based on the NIPA deflators. The first rows of each of table 1's panels confirm that NIPA prices are highly negatively correlated with investment. The second rows indicate that user cost (uc) is weakly correlated with investment in growth rates. Panel A's third row shows that, at business cycle frequencies, non-high-tech equipment investment is highly negatively correlated with its user cost. Panel B's third row shows that this is not true for high-tech investment. However, the fourth rows show that the board's measures of depreciation and taxes offset movements in the rest of user cost. The correlation using non-high-tech equipment's modified user cost (uc*) constructed with the means of the depreciation and tax terms is even stronger. For high-tech investment, fixing depreciation and taxes makes user cost strongly negatively correlated with investment. The findings do not depend on the sample period. Taken together, the findings show that focusing on growth rate correlations places too much weight on high-frequency fluctuations. Long-run identification also deemphasizes high frequencies by focusing on innovations with long-run effects.

C. *Variables Used in the Analysis*

The variables used in the analysis are the growth rates of the investment price and labor productivity, per capita hours, a nominal interest rate, and inflation. The first three variables are the minimum required to identify the effects of the two technology shocks on output and hours, and the last two are included because of the role of monetary policy, discussed below. The GCV real equipment price is used to measure the investment price because it contains more quality adjustment than its NIPA counterpart or either total investment price. Fisher (2005) describes how the main findings are robust to using the GCV-based total investment price and the NIPA counterparts to the GCV prices. Labor productivity is measured by the nonfarm business series published by the Bureau of Labor Statistics (BLS). To retain consistency with the growth model, productivity is expressed in consumption units using the consumption deflator underlying the investment price. Per capita hours are measured with the BLS hours series corresponding to the productivity measure divided by the civilian noninstitutionalized population over the age of 16. The results are robust to using the BLS private business measures of productivity and hours (see Fisher 2005.)

The baseline specification has hours included in log levels. Per capita hours have some low-frequency variation, and the literature is divided about how to deal with this. The main alternatives to the level specification are either to difference or to quadratically detrend log per capita hours (see Francis and Ramey 2005; Galí and Rabanal 2005). The discussion focuses on the level specification because formal tests do not reject it and they do reject the difference specification (see Fisher 2002); it appears to be less prone to specification error (see Christiano et al. 2004), and the quadratic specification has unrealistic long-run implications for hours. However, given the lack of agreement on the issue, the analysis is extended to consider all three specifications together.

For the last two variables, inflation is measured with the consumption deflator underlying the real investment price, and the nominal interest rate is the three-month Treasury bill rate.

V. Findings

The findings are based on a split sample. Fisher (2005) describes full sample results. The four reasons to split the sample stated in Section I are that around 1982 there were significant changes in (i) the investment price's average rate of decline, (ii) the conduct of monetary policy, (iii) macroeconomic volatility, and (iv) the regulatory environment.[13] Since

[13] Regarding reason i, Hornstein and Krusell (1996), Greenwood and Yorukoglu (1997), and Cummins and Violante (2002) discuss changes in the investment price's average rate of decline. A formal analysis based on Bai and Perron's (1998, 2003) methodology points to a single break in 1982. Bai-Perron tests of the null of no change in the real price's mean rate of decline against the alternative of at least one change are rejected at conventional significance levels. Further details are available from the author. Many economists

these changes occur at roughly the same time, it is natural to split the sample to accommodate them all. Galí, López-Salido, and Vallés's (2003) split dates accomplish this: the first subsample is 1955:I–1979:II and the second is 1982:III–2000:IV.[14] The number of lags, N, is four, and where relevant, assumption 3 is imposed with a value of capital's share, α, equal to .25 in (17). This is a compromise between assuming that the equipment price is a proxy for the price of total investment and that it applies only to equipment in a production function that also includes structures. The results are not sensitive to reasonable perturbations of α. The baseline-level specification implies that the combined effect of the technology shocks is large, with investment-specific technology shocks contributing more than neutral shocks. When the two other ways of including hours are considered as well, at least two of three specifications always agree that the total effect of technology shocks is large in each sample. The baseline result on the relative importance of investment-specific shocks is more sensitive to the choice of specification. Subsection *C* argues that the identified shocks reflect technology and not shocks to other variables.

A. *Baseline Estimates*

Figures 4 and 5 display the estimated responses of the investment price, productivity, hours, and output to one-standard-deviation technology shocks for the two subsamples under the *two-technology* assumptions, where both investment-specific and neutral shocks affect productivity in the long run. To assess the impact on inference of adopting the two-technology assumptions, these figures also display responses to N-shocks estimated under the *one-technology* assumption that only neutral shocks affect productivity in the long run. These latter estimates are based on the same variables underlying the two-technology responses, except that the real price is excluded. The solid circles and open circles denote statistical significance at the 5 percent and 10 percent levels.[15]

Consider the two-technology responses for the first subsample depicted in figure 4. After each kind of shock, hours respond by imme-

argue in favor of reason ii. For example, Clarida, Galí, and Gertler (2000) find statistically significant differences in estimates of a Taylor rule for monetary policy before and after Paul Volker's tenure at the Federal Reserve. Stock and Watson (2003*a*, 2003*b*) document reason iii and suggest reason iv as a partial explanation.

[14] The end point of the second subsample is determined by the availability of the GCV equipment deflator. Fisher (2005) describes how the findings are quantitatively similar if the second subsample is extended to the end of 2004 using the NIPA-based counterparts to the GCV-based investment price data.

[15] Statistical significance is calculated by the bootstrap method using Hall (1992) "other-percentile" confidence intervals. Kilian (1999) finds that Hall confidence intervals have good classical coverage probabilities, compared to other bootstrap confidence intervals.

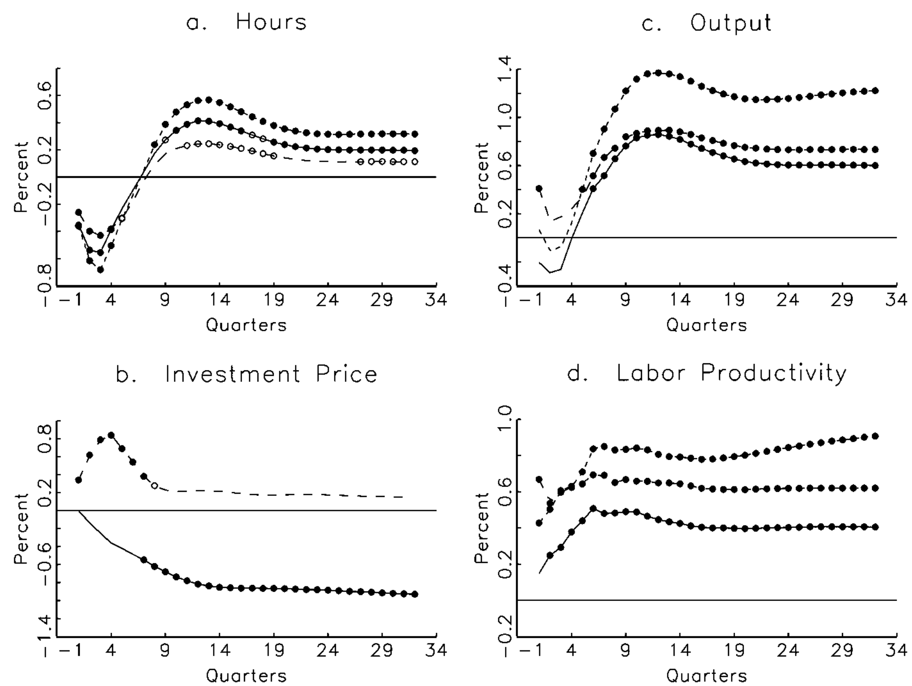

FIG. 4.—Responses to technology shocks, 1955:I–1979:II. Solid lines denote responses to I-shocks in the five-variable system, long-dashed lines responses to N-shocks in the five-variable system, and short-dashed lines responses to N-shocks in the four-variable system. Solid circles indicate that the response is significant at the 5 percent level and open circles at the 10 percent level.

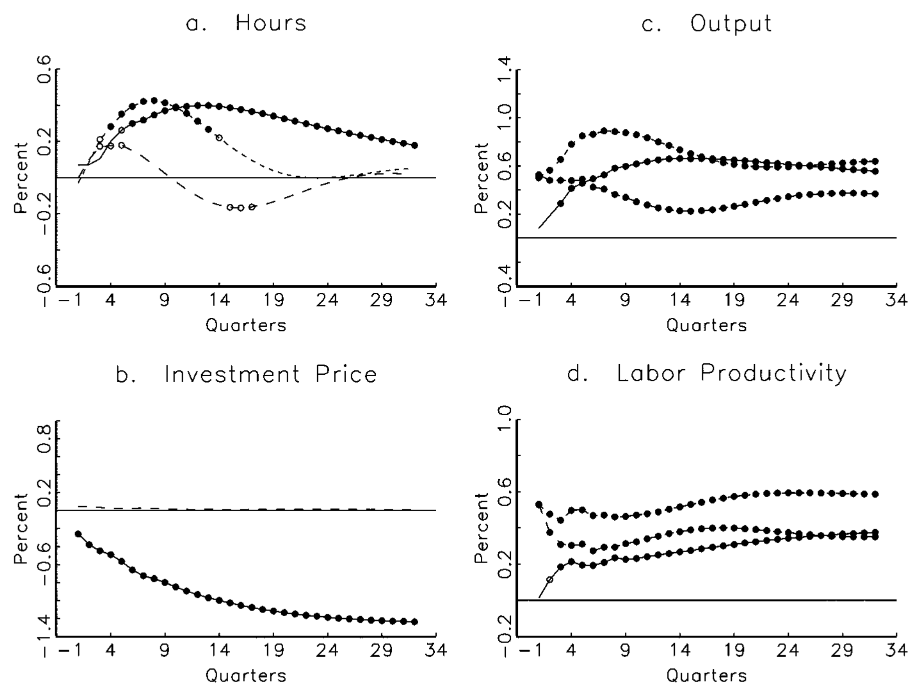

FIG. 5.—Responses to technology shocks, 1982:III–2000:IV. Solid lines denote responses to I-shocks in the five-variable system, long-dashed lines responses to N-shocks in the five-variable system, and short-dashed lines responses to N-shocks in the four-variable system. Solid circles indicate that the response is significant at the 5 percent level and open circles at the 10 percent level.

diately falling, before recovering vigorously and turning positive after about two years. The fall and subsequent increase in hours after both the I- and N-shock (solid and long-dashed lines) are statistically significant at the 5 percent significance level. These hours responses are very similar to those estimated by Shapiro and Watson (1988) with the difference specification. When Shapiro and Watson estimate hours with a trend, hours fall and stay down after a technology shock.

The source of the shock does not matter much for the responses of output and productivity either. Output is insignificant for the first year and is significantly positive thereafter. Productivity rises for a year and a half before leveling out and is always significant at either the 5 percent or 10 percent level. Notice that hours and productivity comove negatively after both shocks in the first year. This does not rule out an important role in short-run fluctuations for the technology shocks in the first subsample, since over this period the unconditional correlation between hours and productivity at business cycle frequencies is also negative.

The responses of the investment price depend more on the source of the shock. After an I-shock, the investment price falls gradually, becoming significant after a year and a half. In contrast, after an N-shock, the price rises significantly before it returns to zero. The investment price response to an N-shock is predicted by a version of the model (1)–(6), extended to include costs of reallocating factors between consumption and investment good production. Taken together, the responses are broadly consistent with the model, except for hours. In this case, the initial decline in hours suggests that productivity should rise initially, as indeed it does after both shocks.

The second subsample two-technology responses depicted in figure 5 are substantially different from their first subsample counterparts, justifying the sample split. After an I-shock, hours responds positively and with a hump shape. The amplitude of this response is clearly lower than in the first subsample, but it is still statistically significant at the 5 percent level. The two-technology hours response to the N-shock is mostly insignificant in the second subsample. The other variable to display large differences across subsamples is the real price. In the first subsample, this rises significantly after an N-shock but is essentially unresponsive in the second subsample.On the basis of the extended model with sectoral adjustment costs described in the previous paragraph, this suggests that the economy more flexibly reallocates factors of production in the second subsample than in the first. As in the first subsample, productivity and output both respond positively and significantly after each shock. The positive comovement between hours and productivity is consistent with the positive correlation between these variables in the second subsample. Overall, in the second subsample the responses are also broadly consistent with theory.

How do the two-technology assumptions affect inference based on the one-technology approach? The Blanchard-Quah aggregation theorem suggests that the combined effects of technology shocks reached using the one-technology assumption should not differ substantially under the two-technology approach if the hours response relative to the productivity response is the same for both technology shocks. Remarkably, this condition roughly holds in a majority of cases in which hours are included in levels, so the one-technology N-shock responses (short-dashed lines) are similar to the sum of the corresponding two-technology responses. The two-technology responses reveal that I-shocks account for much of the underlying technical change identified with the one-technology assumption.

The qualitative similarity between the theoretical and empirical responses provides some confidence that they have been correctly identified (see Galí et al. [2003] for a theory of the initial declines in hours). This justifies taking the next step to consider how these responses translate into contributions to short-run fluctuations. Figure 6 shows actual hours (solid lines) and the historical decompositions of hours derived under the two-technology assumptions for each shock considered on its own.[16] Hours driven by I-shocks track much of the variation in actual hours, particularly around recessions. I-shocks also account for much of the boom of the 1990s, which is consistent with the popular interpretation of this time period. Hours driven by N-shocks do not track actual hours as much. Figures 6*c* and *d* present the business cycle components of actual hours and hours corresponding to the historical decompositions. The variation in hours due to I-shocks is large and is clearly greater than that for N-shocks.[17]

Tables 2 and 3 quantify the findings in figure 6 and provide additional information about output. Table 2 displays the forecast error decomposition of hours and output implied under the one- and two-technology assumptions. The connection between forecast error decompositions and contributions to the business cycle is not direct, so table 3 displays

[16] The predicted time path of hours for a given model and shock is based on simulating (13) using the estimated shocks and the actual data in the first four periods of the sample to initialize the simulation. The deterministic component of hours (the path of hours predicted by the initial conditions) is removed from figs. 6*a* and 6*b*.

[17] Because of the short samples, the business cycle decompositions should be viewed with some caution, especially for the second subsample. The total contribution of technology shocks is exactly equal to the sum of the contributions of the two shocks if the estimated shocks are exactly orthogonal to each other at all leads and lags. The estimation procedure guarantees that the two shocks are orthogonal contemporaneously. In practice, there are slight correlations at various leads and lags. Differences between the sum of the contributions and entries in the first column of table 3 reflect these correlations.

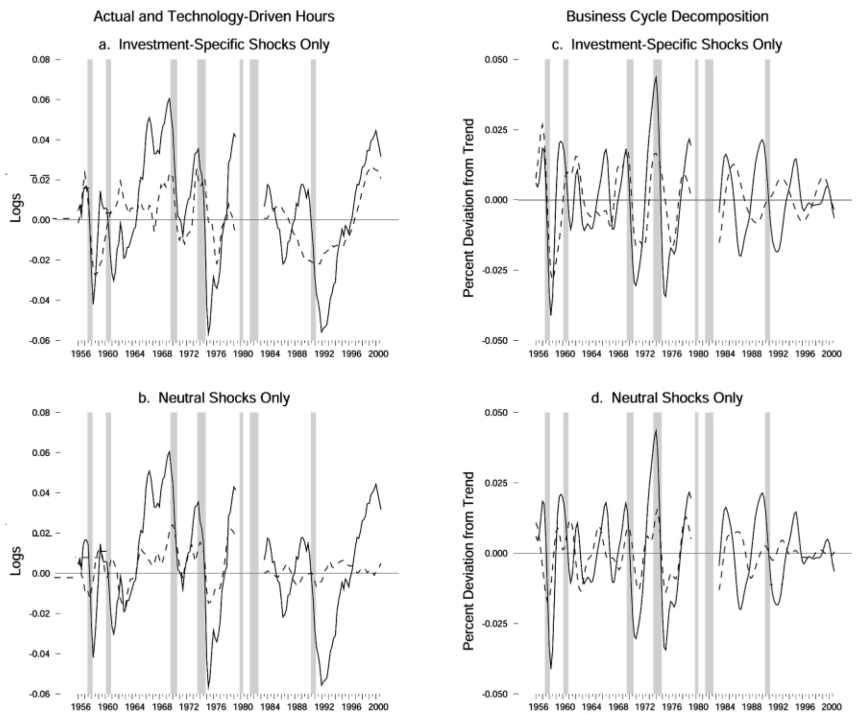

Fig. 6.—Decomposing the contribution of technology shocks to hours. Solid lines denote nonfarm business hours and dashed lines hours due to indicated technology shocks.

TABLE 2
FORECAST ERROR DECOMPOSITIONS (Percent)

Horizon (Quarters)	Hours				Output			
	All Technology	Investment	Neutral	Neutral Only	All Technology	Investment	Neutral	Neutral Only
	A. 1955:I–1979:II							
1	44	29	16	29	15	3	12	0
	(14, 87)	(1, 58)	(0, 31)	(0, 58)	(0, 29)	(0, 6)	(0, 24)	(0, 1)
4	39	24	15	33	9	04	05	1
	(9, 75)	(0, 47)	(0, 30)	(0, 66)	(0, 15)	(0, 7)	(0, 10)	(0, 1)
8	35	20	14	30	34	14	20	33
	(3, 62)	(0, 39)	(0, 28)	(0, 57)	(0, 57)	(0, 38)	(0, 38)	(5, 61)
12	39	25	15	41	58	26	32	63
	(12, 69)	(0, 47)	(0, 28)	(17, 78)	(38, 100)	(0, 51)	(0, 61)	(48, 100)
16	43	28	14	50	68	31	37	74
	(16, 75)	(0, 53)	(0, 28)	(30, 96)	(51, 100)	(0, 59)	(4, 71)	(63, 100)
32	45	30	15	57	79	34	45	86
	(15, 78)	(0, 58)	(0, 28)	(41, 100)	(67, 100)	(0, 66)	(9, 86)	(80, 100)
	B. 1982:III–2000:IV							
1	3	3	0	1	84	2	82	68
	(0, 6)	(0, 7)	(0, 0)	(0, 1)	(69, 100)	(0, 4)	(69, 100)	(39, 100)
4	13	6	7	13	70	16	53	69
	(0, 21)	(0, 11)	(0, 13)	(0, 24)	(45, 100)	(0, 31)	(26, 100)	(46, 100)
8	26	20	6	30	77	34	42	79
	(0, 46)	(0, 38)	(0, 12)	(0, 58)	(59, 100)	(0, 65)	(9, 79)	(63, 100)
12	40	35	5	37	83	49	34	84
	(0, 69)	(0, 65)	(0, 10)	(0, 72)	(70, 100)	(19, 89)	(0, 60)	(72, 100)
16	46	40	6	35	84	57	27	86
	(7, 76)	(1, 74)	(0, 11)	(0, 68)	(72, 100)	(33, 100)	(0, 46)	(75, 100)
32	52	47	6	30	90	65	25	89
	(18, 88)	(10, 86)	(0, 11)	(0, 58)	(82, 100)	(46, 100)	(0, 41)	(81, 100)

NOTE.—Entries are point estimates at a given horizon of the percentage contribution of the indicated shock(s) to the forecast error of hours or output. Entries in parentheses below the point estimates are the associated 95 percent confidence intervals.

TABLE 3
Contribution to the Business Cycle of Technology Shocks (Percent)

Statistic	All Technology	Investment	Neutral	Neutral Only
	A. 1955:I–1979:II			
$\sigma^2_{Hm}/\sigma^2_{Hd}$	73	47	21	77
	(59, 100)	(22, 92)	(0, 39)	(68, 100)
$\sigma^2_{Ym}/\sigma^2_{Yd}$	44	42	8	54
	(12, 83)	(22, 83)	(0, 13)	(35, 100)
	B. 1982:III–2000:IV			
$\sigma^2_{Hm}/\sigma^2_{Hd}$	38	36	15	37
	(0, 66)	(0, 64)	(0, 22)	(0, 67)
$\sigma^2_{Ym}/\sigma^2_{Yd}$	80	67	33	99
	(32, 100)	(43, 100)	(0, 59)	(83, 100)

Note.—Entries are point estimates of the percentage contribution of the indicated shock(s) to the business cycle variation in hours or output. Entries in parentheses below the point estimates are the associated 95 percent confidence intervals.

the ratio of the business cycle variances of the technology shock–only driven data to the variance of actual hours and output. In both tables, the entries are point estimates, and the associated 95 percent confidence intervals are in parentheses.

Panel A of table 2 shows that in the first subsample, 35–45 percent of hours' forecast error over eight years is accounted for by the two technology shocks. I-shocks are about twice as important as N-shocks. Over the first four quarters, technology shocks account for a small fraction of output's forecast error. After a year the contributions rise quickly and range from 34 percent to 79 percent. N-shocks account for slightly more than I-shocks in the first subsample. Panel B shows that the two technology shocks account for a large fraction of the forecast error of both output and hours in the second subsample as well. For hours, the contributions exceed 40 percent after three years, and for output, the contributions are all above 69 percent and rise as high as 90 percent. As in the first subsample, I-shocks are more important than N-shocks for hours. After three years, I-shocks also contribute more to output fluctuations. In confirmation of the previous visual inspection of the Blanchard-Quah conditions, the one-technology assumption is nearly sufficient for identifying the total contribution of technology. Still, the two-shock assumptions show that the majority of technology's contribution comes from investment-specific technical change. The confidence intervals show that there is often a lot of uncertainty about the true magnitudes of the decompositions. However, the combined contributions of the technology shocks are significant after three years in all but one case. For the exception, hours in the second subsample, the combined contribution is significant after four years.

Table 3 indicates that at business cycle frequencies, technology shocks are important for both hours and output in both subsamples. The two technology shocks account for 73 percent and 38 percent of the variation of hours in the two samples and 44 percent and 80 percent for output. Three of the four variance ratios are statistically significant. I-shocks account for the majority of the business cycle variation of both hours and output in both samples.

Tables 2 and 3 describe the share of the variation in hours and output that is due to technology shocks. Another way to gauge the importance of the shocks is to consider how much they contribute to the decline in aggregate volatility in the second subsample. A key difference between the two subsamples is the decline in amplitude of the variables' responses to the shocks in the second subsample. The source of this decline is that the shocks are estimated to be much less volatile in the second subsample. In the first subsample, the estimated standard deviations are 1.16 percent and 1.15 percent for the I-shock and N-shock; in the second subsample, they are 0.33 percent and 0.50 percent. Suppose, for example, that the I-shock was just as volatile in the second subsample as in the first. This implies that the peak response of hours in the second subsample would have been 1.4 percent instead of 0.4 percent. This increase in amplitude translates into raising the variance of hours' unforecastable component by a factor of 3.5, suggesting that the decline in aggregate volatility might be due in large part to the I-shocks' decline in variance.[18]

B. *Adding the Difference and Detrended Specifications to the Analysis*

This subsection adds the difference and detrended specifications to the analysis. Figures 7 and 8 display the hours and output responses to the technology shocks under the two-technology assumptions for the three specifications. Statistical significance for the level specification (solid lines) is indicated in figures 4 and 5, and for the other specifications it is indicated as in those figures. In contrast with the levels case, the difference (long-dashed lines) and detrended estimates (short-dashed lines) are often not significant.

Figures 7 and 8 show that at least one of the specifications is similar to the level case in each of the samples. The detrended case is closest to the baseline in the first subsample, and the difference case is closest in the second. The exception to this generalization is the response of hours to an N-shock in the second subsample, when hours are differenced. In this case there is a large negative response, whereas the re-

[18] Justiniano and Primiceri (2006) reach a similar conclusion using a fully specified structural model.

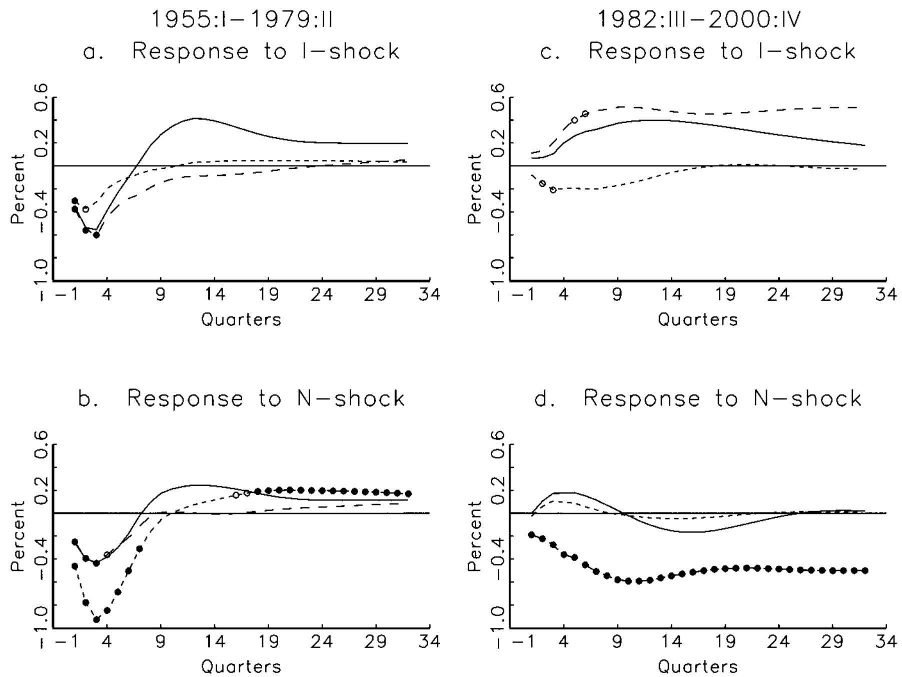

FIG. 7.—Hours responses for the three specifications. Solid lines denote the levels point estimate, long-dashed line the difference point estimate with indication of significance. and short-dashed line the detrended point estimate with indication of significance. Solid circles indicate that the response is significant at the 5 percent level and open circles at the 10 percent level.

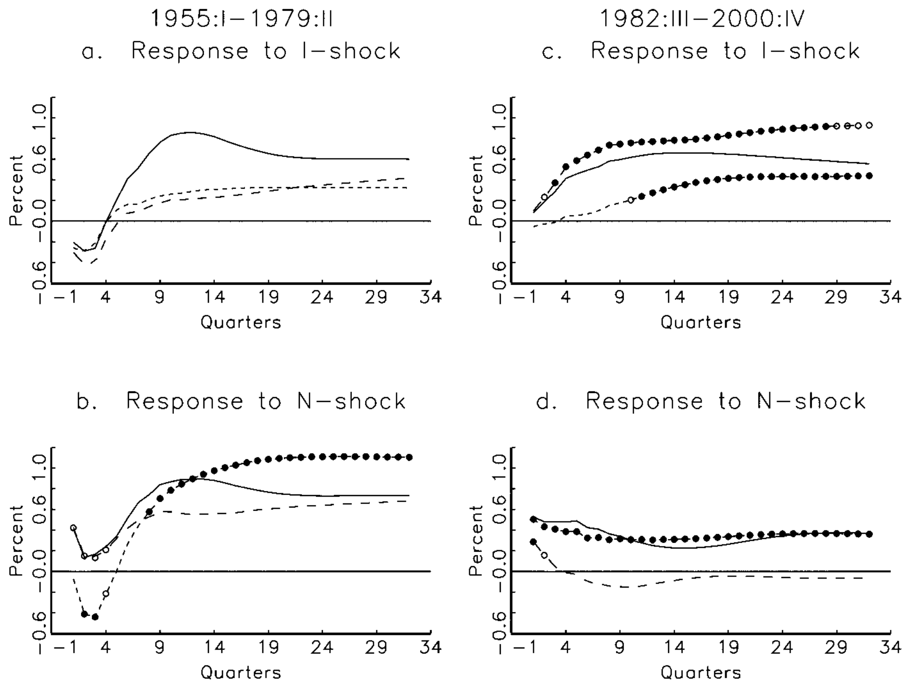

FIG. 8.—Output responses for the three specifications. Solid lines denote the levels point estimate, long-dashed line the difference point estimate with indication of significance, and short-dashed line the detrended point estimate with indication of significance. Solid circles indicate that the response is significant at the 5 percent level and open circles at the 10 percent level.

sponse is essentially zero for both the level and detrended cases. Over the full sample, the three specifications do not agree on the sign of the response of hours to an N-shock under the one-technology assumption (see Christiano et al. 2004). In contrast, in the first subsample, all three specifications agree that hours falls after a technology shock.

Tables 4 and 5 display the forecast error decompositions for hours and output.[19] The business cycle decompositions lead to similar conclusions and are not displayed. Technology shocks have large overall effects on both output and hours with detrended hours in the first subsample and with the difference specification in the second subsample. The detrended case has large technology effects on output in the second subsample. In the first subsample, the detrended specification implies that the two technology shocks account for over 50 percent of hours' and from 33 to 77 percent of output's forecast errors from three to eight years. In the second subsample, the difference specification says that the technology shocks account for 39–47 percent of hours' and 41–56 percent of output's forecast errors from three to eight years. The detrended case implies that technology shocks account for 45–81 percent of output's forecast errors for all horizons in the second subsample. The level finding that the contribution of I-shocks exceeds that of N-shocks holds for the difference case in the second subsample, but not when hours are detrended in the first subsample. In the cases that agree with the level specification, the uncertainty in the estimates is similar to that for the level specification.

Tables 4 and 5 also indicate that there is less Blanchard-Quah aggregation with the nonlevel specifications. In the first subsample, the one-technology detrended specification does quite well predicting the total contribution of technology shocks. However, table 5 indicates that in the second subsample, the one-technology cases all underpredict the total contribution of technology shocks. In the second subsample, the one-technology difference case demonstrates that by excluding the investment price and ignoring the possibility of I-shocks, Galí et al. (2003) substantially underpredict the contribution of technology shocks.

C. *Are the Shocks Technology?*

This subsection assesses the plausibility of the identified technology shocks by subjecting them to additional tests. Following Evans (1994),

[19] Galí and Rabanal (2005) display results on the contribution of I-shocks and N-shocks using the three transformations of hours and four different underlying hours measures. They find much smaller contributions to business cycles for the difference and detrended cases. Their findings are based on a VAR including just hours, productivity, and the real price and that is estimated over the full sample. They also do not assess whether or not assumption 3 holds.

TABLE 4
Error Decompositions Including Hours in Other Ways, 1955:I–1979:II (Percent)

Horizon (Quarters)	Hours: All Technology	Hours: Investment	Hours: Neutral	Hours: Neutral Only	Output: All Technology	Output: Investment	Output: Neutral	Output: Neutral Only
	A. Difference							
1	43	30	13	61	17	6	11	2
	(4, 85)	(0, 60)	(0, 26)	(36, 1)	(0, 33)	(0, 12)	(0, 23)	(0, 5)
4	28	18	10	49	8	5	3	8
	(0, 52)	(0, 35)	(0, 19)	(20, 97)	(0, 13)	(0, 10)	(0, 5)	(0, 15)
8	18	12	6	37	10	3	7	6
	(0, 31)	(0, 22)	(0, 11)	(3, 72)	(0, 14)	(0, 5)	(0, 12)	(0, 09)
12	15	10	5	31	15	3	12	8
	(0, 24)	(0, 18)	(0, 9)	(0, 62)	(0, 27)	(0, 5)	(0, 22)	(0, 13)
16	13	9	4	28	19	4	15	11
	(0, 20)	(0, 16)	(0, 8)	(0, 54)	(0, 27)	(0, 6)	(0, 28)	(0, 19)
32	9	6	3	19	32	7	25	31
	(0, 12)	(0, 10)	(0, 5)	(0, 36)	(0, 50)	(0, 12)	(0, 45)	(0, 55)
	B. Detrended							
1	66	20	46	56	5	5	.01	6
	(42, 100)	(0, 40)	(33, 92)	(25, 1)	(0, 9)	(0, 9)	(0, 1)	(0, 12)
4	59	8	51	54	9	3	6	10
	(36, 100)	(0, 15)	(36, 1)	(26, 1)	(0, 15)	(0, 5)	(0, 12)	(0, 18)
8	52	6	46	46	14	3	11	15
	(25, 98)	(0, 10)	(29, 91)	(16, 90)	(0, 20)	(0, 5)	(0, 20)	(0, 25)
12	50	6	44	44	33	5	29	33
	(21, 93)	(0, 9)	(27, 87)	(15, 86)	(0, 53)	(0, 8)	(0, 54)	(0, 57)
16	50	6	44	45	50	6	44	49
	(22, 92)	(0, 9)	(27, 87)	(16, 87)	(16, 85)	(0, 10)	(15, 84)	(19, 89)
32	52	5	47	49	77	7	70	77
	(25, 96)	(0, 8)	(32, 92)	(24, 94)	(64, 100)	(0, 12)	(58, 100)	(64, 100)

Note.—See the note to table 2.

TABLE 5
PERCENTAGE FORECAST ERROR DECOMPOSITIONS INCLUDING HOURS IN OTHER WAYS, 1982:III–2000:IV (Percent)

Horizon (Quarters)	Hours: All Technology	Hours: Investment	Hours: Neutral	Hours: Neutral Only	Output: All Technology	Output: Investment	Output: Neutral	Output: Neutral Only
				A. Difference				
1	36	9	27	33	28	3	25	32
	(0, 71)	(0, 19)	(0, 54)	(0, 65)	(0, 51)	(0, 6)	(0, 50)	(0, 65)
4	27	10	17	10	26	21	5	14
	(0, 50)	(0, 20)	(0, 33)	(0, 20)	(0, 45)	(0, 42)	(0, 8)	(0, 27)
8	33	15	18	6	34	32	2	11
	(0, 62)	(0, 30)	(0, 36)	(0, 12)	(0, 61)	(0, 63)	(0, 3)	(0, 21)
12	39	17	22	6	41	39	2	10
	(0, 72)	(0, 34)	(0, 43)	(0, 12)	(0, 74)	(0, 77)	(0, 3)	(0, 19)
16	42	19	24	7	46	44	2	10
	(2, 77)	(0, 36)	(0, 47)	(0, 13)	(2, 83)	(6, 87)	(0, 3)	(0, 19)
32	47	22	24	8	56	55	1	11
	(5, 85)	(0, 42)	(0, 49)	(0, 16)	(19, 100)	(21, 100)	(0, 1)	(0, 22)
				B. Detrended				
1	5	4	0	21	78	1	76	30
	(0, 8)	(0, 8)	(0, .1)	(0, 42)	(58, 100)	(0, 2)	(60, 100)	(0, 60)
4	12	10	2	8	48	.00	47	23
	(0, 21)	(0, 19)	(0, 4)	(0, 15)	(8, 84)	(.00, .00)	(9, 82)	(0, 45)
8	12	11	2	5	45	2	43	33
	(0, 21)	(0, 21)	(0, 3)	(0, 10)	(2, 77)	(0, 3)	(9, 82)	(0, 65)
12	14	13	2	5	53	7	46	47
	(0, 23)	(0, 24)	(0, 2)	(0, 10)	(17, 84)	(0, 13)	(14, 84)	(7, 48)
16	14	13	2	5	62	16	45	58
	(0, 22)	(0, 24)	(0, 3)	(0, 9)	(33, 91)	(0, 30)	(13, 77)	(26, 96)
32	14	12	2	5	81	39	43	76
	(0, 21)	(0, 22)	(0, 3)	(0, 9)	(67, 100)	(9, 71)	(3, 68)	(59, 100)

NOTE.—See the note to table 2.

TABLE 6
GRANGER-CAUSALITY TESTS

Technology Shock	Capital Tax Changes	Federal Funds Rate	Hoover-Perez Oil Dates	Military Spending Changes
		A. 1955:I–1979:II		
Investment-specific	7	93	4.6	17
Neutral	82	82	15	23
Neutral only	49	99	52	12
		B. 1982:III–2000:IV		
Investment-specific	55	97	*	14
Neutral	17	91	*	42
Neutral only	27	98	*	74

NOTE.—The table reports probabilities (in percent) that an F-distributed random variable exceeds the F-statistic associated with the variable in question. The F-test is based on a regression of the identified technology shock on a constant and current and four quarterly lags of the variable in question, except the federal funds rate, for which no current value is included. The null hypothesis is that all the coefficients on the variable in question are jointly equal to zero.
* There are not enough observations of the variable in question to compute a meaningful test.

Francis and Ramey (2005) propose examining the plausibility of identified technology shocks by testing whether other variables Granger-cause them. If the shocks are truly due to *exogenous* technical innovations, then other variables should not predict them. This subsection considers whether the federal funds rate, Hoover and Perez's (1994) oil shock dates, changes in the log of real military spending, and changes in the average capital tax rate Granger-cause the baseline identified technology shocks (the results are similar for the difference and detrended ways of including hours). The first three variables are included because they are commonly associated with short-run fluctuations. The fourth variable is included since theory predicts that permanent changes in capital taxes have permanent effects on labor productivity and the investment price.[20]

Table 6 reports marginal probabilities associated with F-tests, each based on a regression of the indicated technology shock on a constant, current values, and four lags of the variable in question, except for the federal funds rate, where no current value is included because monetary policy can respond swiftly to shocks within a quarter. The null hypothesis is that all the coefficients on the variable in question are jointly equal to zero. The asterisks for the oil dates in the second subsample indicate that no test is conducted because there are only two dates in this period.

[20] If a proportional capital income tax is added to the model of Sec. II, a permanent increase in the tax lowers labor productivity in the long run. If the model is extended to include separate consumption and investment good sectors, with capital's share in the consumption sectors higher than in the investment sector, then a permanent increase in the capital tax raises the real investment price in the long run.

The table indicates that in only one case is the null hypothesis of no Granger-causality rejected at the 5 percent significance level. It is never rejected for the capital tax, the federal funds rate, or military spending. Granger-causality is marginally rejected for I-shocks at the 5 percent level with the oil dates in the second subsample. The oil shock result might not be surprising. Suppose that an exogenous increase in the price of oil induces substitution toward equipment that the United States is not good at producing, such as high-mileage cars. If this is the case, then the real price of equipment rises. From this perspective, a permanent oil shock is very much like an I-shock.

VI. Conclusions

This paper argues that when one takes into account investment-specific technical change, technology shocks have large effects on short-run fluctuations. In the preferred level specification, the two technology shocks combined account for 73 percent and 44 percent of the business cycle variation of hours and output in the pre-1982 sample and 38 percent and 80 percent after 1982. The two shocks also account for more than 40 percent and 58 percent of hours' and output's forecast errors over a horizon of three to eight years in both samples. The investment-specific shocks account for the majority of the effects. The alternative specifications considered provide less clear-cut evidence on the role of the technology shocks. While technology shocks typically are found to have a prominent role in explaining hours and output fluctuations, there are some exceptions, and each of the alternative specifications includes at least one case in which the results assign less importance to technology shocks than in the preferred specification. Evidence is presented that the identified shocks reflect technology and not shocks to other variables.

Since the results are based on a procedure that abstracts from transitory technology shocks, they represent a lower bound on the overall contribution of technology shocks to short-run fluctuations. Therefore, the results suggest that technology shocks, or more generally shocks to the efficiency of producing goods, could be important for understanding short-run fluctuations. The finding that investment-specific shocks contribute a lot to the overall effects of technology suggests that business cycle research might benefit from being directed toward studying these shocks and other factors that influence the efficiency of producing investment goods relative to consumption goods. It is also worth exploring other measures of neutral and investment-specific technical change such as those in Basu et al. (2005). Since the split sample introduces additional uncertainty over the magnitudes of the effects, it is also worth exploring other econometric approaches to structural change.

Appendix A

Restricting Labor Productivity's Response to an I-Shock

Recall that the moving average representation of the model is

$$\begin{aligned} \mathbf{y}_t &= \mathbf{\Phi}(L)\boldsymbol{\epsilon}_t \\ &= \mathbf{C}(L)^{-1}\boldsymbol{\epsilon}_t, \end{aligned}$$

where $\mathbf{C}(L) \equiv \mathbf{A} - \mathbf{\Gamma}(L)L$. The long-run effects of innovations to the fundamental shocks are given by $\mathbf{\Phi}(1) = \mathbf{C}(1)^{-1}$. Assumptions 1 and 2 imply

$$\mathbf{C}(1)^{-1} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & \cdots & 0 \\ a_{21} & a_{22} & 0 & 0 & \cdots & 0 \\ a_{31} & a_{32} & a_{33} & a_{34} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & a_{n4} & \cdots & a_{nn} \end{bmatrix},$$

where the a_{ij} terms are real scalars. Assumption 3 implies $a_{11}/a_{21} = -(1-\alpha)/\alpha$.

Let the ijth element of $\mathbf{C}(1)$ be denoted c_{ij}. Recall that the ijth element of the inverse of a matrix equals $(-1)^{i+j}M_{ji}$ divided by the determinant of the matrix to be inverted, where M_{ji} is the minor of the jith element of the matrix to be inverted. Using this formula, we have

$$c_{21} = -\det\begin{bmatrix} a_{21} & 0 & 0 & \cdots & 0 \\ a_{31} & a_{33} & a_{34} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n3} & a_{n4} & \cdots & a_{nn} \end{bmatrix} = -a_{21}\det\begin{bmatrix} a_{33} & a_{34} & \cdots & a_{3n} \\ a_{43} & a_{44} & \cdots & a_{4n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n3} & a_{n4} & \cdots & a_{nn} \end{bmatrix}$$

and

$$c_{22} = \det\begin{bmatrix} a_{11} & 0 & 0 & \cdots & 0 \\ a_{31} & a_{33} & a_{34} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n3} & a_{n4} & \cdots & a_{nn} \end{bmatrix} = a_{11}\det\begin{bmatrix} a_{33} & a_{34} & \cdots & a_{3n} \\ a_{43} & a_{44} & \cdots & a_{4n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n3} & a_{n4} & \cdots & a_{nn} \end{bmatrix}.$$

Notice that the determinants on the right-hand side of these two sets of equalities are identical. This means that

$$-\frac{a_{11}}{a_{21}} = \frac{c_{22}}{c_{21}}.$$

It follows that assumption 3 holds if and only if

$$\frac{1-\alpha}{\alpha}c_{21} - c_{22} = 0.$$

Appendix B

Detailed Data Sources

Since the GCV equipment deflator is an annual series, it must be interpolated. This paper uses Denton's (1971) method, which uses information in a higherfrequency indicator variable to interpolate a better-quality but lower-frequency variable. The method involves minimizing the squared differences of successive ratios of the interpolated to the indicator series subject to the constraint that the sum or average of the interpolated series equals the value in the annual series.[21] The GCV equipment-specific deflator is the annual GCV deflator interpolated with the NIPA equipment deflator under the assumption that the average price for the year must equal the GCV annual deflator. The GCV total investment deflator is computed by using the NIPA's chain-weighting procedure to combine the GCV equipment-specific deflator with the NIPA deflators for nonresidential structures, residential structures, consumer durables, and government investment. The NIPA equipment deflator is taken directly from the national accounts. The NIPA total investment deflator is the same as the GCV total investment deflator except that the interpolated GCV equipment series is replaced by the NIPA equipment deflator.

Gordon (1989) estimates an annual quality-adjusted consumer durables deflator that also indicates considerable quality bias in the corresponding NIPA deflator. The consumer durable deflator is used in the construction of the total investment deflator and is the price used for the service flow from durables in the consumption deflator. The annual Gordon consumer durable deflator is interpolated using the NIPA deflator as the related series for the period 1947–83, and this is spliced to the NIPA deflator for the remaining years of the sample. In the last few years in which there is overlap between the Gordon series and the NIPA series, the growth rates of the series are virtually identical.

For each data series below, there is a brief description of its construction. In cases in which it is relevant, the data codes from the Haver Analytics Database, where the series was obtained, are displayed in parentheses. To be consistent with the GCV equipment deflator, the NIPA series are those prior to the 2004 revisions, available as of October 2002. The overall sample period is 1955:I–2000:IV. The end point of the sample is determined by the availability of the GCV equipment deflator.

- The consumption deflator is computed by chain-weighting the deflators for nondurables consumption (CN/CNH) plus services consumption (CS/CSH) plus government consumption (the chain-weighted sum of GFDE/GFDH, GFNE/GFNEH, and GSE/GSEH) plus the service flow from consumer durables (chain-weighted real service flow obtained from David Reifschneider at the Board of Governors, converted to nominal terms with the price index for durable consumption goods described above; the NIPA durables deflator is CD/CDH).
- Per capita nonfarm hours is nonfarm business hours (LXNFH) divided by the noninstitutional civilian population 16 years and over (LN16N, adjusted at the Federal Reserve Bank of Chicago to smooth out various discrete revisions made by the Census Bureau). Nominal nonfarm business real output is nonfarm business output (LXNFO) multiplied by the deflator for that output (LXNFI). Nonfarm business labor productivity in consumption units is real nonfarm labor productivity (LXNFA) multiplied by

[21] When the related series is a good indicator, the practical differences among different interpolation-by-related series methods are small. An extensive discussion of alternative interpolation methods can be found in the *Handbook of Quarterly National Accounts Compilation*, available at http://www.imf.org/external/pubs/ft/qna/2000/Textbook/index.htm.

the deflator for nonfarm business output (LXNFI) divided by the consumption deflator.

- The total investment deflator is computed by chain-weighting the deflators for private nonresidential structures investment (FNS/FNSH), private equipment investment (the GCV deflator described above), private residential structures investment (FR/FRH), expenditures on consumer durables (the deflator described above), and government investment (the chain-weighted sum of GFDI/GFDIH, GFNI/GFNIH, and GSI/GSIH). The real total investment price is the ratio of the total investment deflator and the consumption deflator. The real equipment price is the ratio of the GCV equipment deflator described above and the consumption deflator.
- The interest rates used are the federal funds rate (FFED) and the yield on three-month Treasury bills (FTBS3). The capital tax series is taken from Burnside, Eichenbaum, and Fisher (2004).

References

Alvarez, Fernando, and Urban J. Jermann. 2005. "Using Asset Prices to Measure the Persistence of the Marginal Utility of Wealth." *Econometrica* 73 (November): 1977–2016.

Bai, Jushan, and Pierre Perron. 1998. "Estimating and Testing Linear Models with Multiple Structural Changes." *Econometrica* 66 (January): 47–78.

———. 2003. "Computation and Analysis of Multiple Structural Change Models." *J. Appl. Econometrics* 18 (January–February): 1–22.

Basu, Susanto, and John G. Fernald. 2002. "Aggregate Productivity and Aggregate Technology." *European Econ. Rev.* 46 (June): 963–91.

Basu, Susanto, John G. Fernald, Jonas D. M. Fisher, and Miles Kimball. 2005. "Sectoral Technical Change." Manuscript, Fed. Reserve Bank San Francisco.

Basu, Susanto, John G. Fernald, and Miles Kimball. 2004. "Are Technology Improvements Contractionary?" Working Paper no. 10592 (June), NBER, Cambridge, MA.

Blanchard, Olivier J., and Danny Quah. 1989. "The Dynamic Effects of Aggregate Demand and Supply Disturbances." *A.E.R.* 79 (September): 655–73.

Boldrin, Michele, Lawrence J. Christiano, and Jonas D. M. Fisher. 2001. "Habit Persistence, Asset Returns, and the Business Cycle." *A.E.R.* 91 (March): 149–66.

Burnside, Craig, Martin Eichenbaum, and Jonas D. M. Fisher. 2004. "Fiscal Shocks and Their Consequences." *J. Econ. Theory* 115 (March): 89–117.

Campbell, Jeffrey R. 1998. "Entry, Exit, Embodied Technology, and Business Cycles." *Rev. Econ. Dynamics* 1 (April): 371–408.

Christiano, Lawrence J., Martin Eichenbaum, and Robert Vigfussen. 2004. "What Happens after a Technology Shock?" Manuscript, Northwestern Univ.

———. 2006. "Assessing Structural VARs." Manuscript, Northwestern Univ.

Christiano, Lawrence J., and Jonas D. M. Fisher. 1998. "Stock Market and Investment Good Prices: Implications for Macroeconomics." Working Paper no. 98-6, Fed. Reserve Bank Chicago.

Christiano, Lawrence J., and Terry J. Fitzgerald. 2003. "The Band Pass Filter." *Internat. Econ. Rev.* 44 (May): 435–65.

Clarida, Richard, Jordi Galí, and Mark Gertler. 2000. "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory." *Q.J.E.* 115 (February): 147–80.

Cooley, Thomas F., and Mark Dwyer. 1998. "Business Cycle Analysis without Much Theory: A Look at Structural VARs." *J. Econometrics* 83 (March–April): 57–88.

Cummins, Jason G., and Giovanni L. Violante. 2002. "Investment-Specific Technical Change in the United States (1947–2000): Measurement and Macroeconomic Consequences." *Rev. Econ. Dynamics* 5 (April): 243–84.

Denton, Frank T. 1971. "Adjustment of Monthly or Quarterly Series to Annual Totals: An Approach Based on Quadratic Minimization." *J. American Statis. Assoc.* 66 (March): 99–102.

Erceg, Christopher J., Luca Guerriera, and Christopher Gust. 2004. "Can Long-Run Restrictions Identify Technology Shocks?" Manuscript, Board Governors, Fed. Reserve System, Washington, DC.

Evans, Charles L. 1994. "Productivity Shocks and Real Business Cycles." *J. Monetary Econ.* 29 (April): 191–208.

Fernandez-Villaverde, Jesus, Juan Rubio-Ramirez, and Thomas J. Sargent. 2004. "A, B, C, (and D)'s for Understanding VARs." Manuscript, New York Univ.

Fisher, Jonas D. M. 1997. "Relative Prices, Complementarities and Comovement among Components of Aggregate Expenditures." *J. Monetary Econ.* 39 (August): 449–74.

———. 2003. "Technology Shocks Matter." Working Paper no. 2002-14 (rev.), Fed. Reserve Bank Chicago.

———. 2005. "The Dyanamic Effects of Neutral and Investment-Specific Technology Shocks." Manuscript, Fed. Reserve Bank Chicago.

Francis, Neville, and Valerie A. Ramey. 2005. "Is the Technology-Driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited." *J. Monetary Econ.* 52 (November): 1379–99.

Galí, Jordi. 1999. "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *A.E.R.* 89 (March): 249–71.

Galí, Jordi, J. David López-Salido, and Javier Vallés. 2003. "Technology Shocks and Monetary Policy: Assessing the Fed's Performance." *J. Monetary Econ.* 50 (May): 723–43.

Galí, Jordi, and Pau Rabanal. 2005. "Technology Shocks and Aggregate Fluctuations: How Well Does the RBC Model Fit Postwar U.S. Data?" In *NBER Macroeconomics Annual 2004*, edited by Mark Gertler and Kenneth Rogoff. Cambridge, MA: MIT Press.

Gordon, Robert J. 1989. *The Measurement of Durable Goods Prices.* Chicago: Univ. Chicago Press.

Gort, Michael, Jeremy Greenwood, and Peter Rupert. 1999. "Measuring the Rate of Technological Progress in Structures." *Rev. Econ. Dynamics* 2 (January): 207–30.

Greenwood, Jeremy, Zvi Hercowitz, and Gregory W. Huffman. 1988. "Investment, Capacity Utilization, and the Business Cycle." *A.E.R.* 78 (June): 402–17.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell. 1997. "Long-Run Implications of Investment-Specific Technological Change." *A.E.R.* 87 (June): 342–62.

———. 2000. "The Role of Investment-Specific Technological Change in the Business Cycle." *European Econ. Rev.* 44 (January): 91–115.

Greenwood, Jeremy, and Mehmet Yorukoglu. 1997. "1974." *Carnegie-Rochester Conf. Ser. Public Policy* 46 (June): 49–95.

Hall, Peter. 1992. *The Bootstrap and Edgeworth Expansion.* New York: Springer-Verlag.

Hassett, Kevin A., and R. Glenn Hubbard. 2002. "Tax Policy and Business Investment." In *Handbook of Public Economics*, vol. 3, edited by Alan J. Auerbach and Martin Feldstein. Amsterdam: Elsevier Sci.

Hoover, Kevin D., and Stephen J. Perez. 1994. "Post Hoc Ergo Propter Once More: An Evaluation of 'Does Monetary Policy Matter?' in the Spirit of James Tobin." *J. Monetary Econ.* 34 (August): 47–73.

Hornstein, Andreas, and Per Krusell. 1996. "Can Technology Improvements Cause Productivity Slowdowns?" In *NBER Macroeconomics Annual 1996*, edited by Ben S. Bernanke and Julio J. Rotemberg. Cambridge, MA: MIT Press.

Justiniano, Alejandro, and Giorgio E. Primiceri. 2006. "The Time Varying Volatility of Macroeconomic Fluctuations." Manuscript, Northwestern Univ.

Kilian, Lutz. 1999. "Finite-Sample Properties of Percentile and Percentile-*t* Bootstrap Confidence Intervals for Impulse Responses." *Rev. Econ. and Statis.* 81 (November): 652–60.

King, Robert G., Charles I. Plosser, James H. Stock, and Mark W. Watson. 1991. "Stochastic Trends and Economic Fluctuations." *A.E.R.* 81 (September): 819–40.

Moulton, Brent R. 2001. "The Expanding Role of Hedonic Methods in the Official Statistics of the United States." Manuscript, Bur. Econ. Analysis, Washington, DC.

Prescott, Edward C. 1986. "Theory ahead of Business Cycle Measurement." *Fed. Reserve Bank Minneapolis Q. Rev.* 10 (Fall): 9–22.

Ramey, Valerie A. 1996. "Comment on 'Can Technology Improvements Cause Productivity Slowdowns?'" In *NBER Macroeconomics Annual 1996*, edited by Ben S. Bernanke and Julio J. Rotemberg. Cambridge, MA: MIT Press.

Shapiro, Matthew D., and Mark W. Watson. 1988. "Sources of Business Cycle Fluctuations." In *NBER Macroeconomics Annual 1988*, edited by Stanley Fischer. Cambridge, MA: MIT Press.

Stock, James H., and Mark W. Watson. 2003*a*. "Has the Business Cycle Changed and Why?" In *NBER Macroeconomics Annual 2002*, edited by Mark Gertler and Kenneth Rogoff. Cambridge, MA: MIT Press.

———. 2003*b*. "Has the Business Cycle Changed? Evidence and Explanations." Manuscript, Princeton Univ.