Federal Reserve Bank of Chicago

Technology Shocks Matter

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Abstract

I use the neoclassical growth model to identify the effects of technology shocks on the US business cycle. The model includes two sources of technology shocks: neutral, which affect the production of all goods homogeneously, and investment-specific. Investment-specific shocks are the unique source of the secular trend in the real price of investment goods, while both shocks are the only factors which affect labor productivity in the long run. Consistent with previous empirical work which considers only neutral shocks, the results suggest these shocks account for little, about 6 percent, of the business cycle variation in hours worked. In contrast, investment-specific shocks account for about 50 percent, a new finding which suggests that technology shocks are an important source of the business cycle.

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1. Introduction

This paper shows that investment-specific technology shocks account for a significant fraction of the business cycle. In doing so it overturns recent conclusions, based on research which focuses on neutral technological change, that technology shocks are unimportant for the business cycle.

Traditional estimates of the technology-driven business cycle are based on *transitory* neutral technology shocks derived from Solow residuals. Many researchers view these estimates to be implausibly large since Solow residuals are an error-ridden measure of neutral technology over short horizons. If transitory shocks are implausible, and one only considers neutral technological change, then *permanent* neutral shocks are the remaining source for a technology-driven business cycle. Permanent neutral shocks can be identified without relying on Solow residuals, under the assumption that they are the only source of permanent shocks to labor productivity. Galí (1999) and a growing literature use this approach and find that technology shocks account for very little of the business cycle. The robustness of this finding and the likely irrelevance of transitory shocks suggest that technology shocks are unimportant for the business cycle.[1]

The contribution of this paper is to demonstrate that the data strongly suggest otherwise. Permanent technology shocks matter after all, if one also considers investment-specific technological change. The findings in Greenwood, Hercowitz and Krusell (1997) motivate considering this additional source of technological change. Using evidence on the secular decline in the real investment price, these authors show that investment-specific, not neutral, technological change, is the major source of economic growth. From the real business cycle perspective, if investment-specific technological change is important for growth, it could also be important for the business cycle.

[1] For a recent examination of the difficulties involved with measuring transitory fluctuations in neutral technology, see Basu and Fernald (2001, 2002). Figure 6, p. 268 is the clearest statement of the finding that technology shocks do not matter in Gali (1999). Recent papers by Francis and Ramey (2001) and Christiano, Eichenbaum and Vigfusson (2002), Gali (2003) confirm the finding. This research builds on Blanchard and Quah (1989), King, Plosser, Stock and Watson (1991), and Shapiro and Watson (1988).

To assess this possibility, I adapt the framework that has been used to estimate the contribution of permanent neutral technology shocks to the business cycle. First, consistent with the neoclassical growth model, I modify the standard assumption that neutral technological change is the only source of long run changes in labor productivity to include the possibility that investment-specific change also has an effect. Second, I impose the additional restriction, also implied by the growth model, that investment-specific technological change is the unique source of the secular trend in the real price of investment goods. These assumptions are sufficient to identify the business cycle effects of both kinds of technological change.

When I impose these assumptions on US data I reproduce the standard result that neutral technological change is relatively unimportant for explaining the business cycle, accounting for less than 10 percent of business cycle variation in hours worked. In contrast, I also find that investment-specific technological change accounts for about 50 percent of this variation. Therefore, in total, technology shocks account for a significant fraction of the business cycle variation in hours worked. I show that this basic finding is robust to many perturbations of the analysis, including alternative empirical specifications and sample periods. In addition, I show that the shocks I identify are unrelated to other variables, such as capital taxes, that might have affected labor productivity and the real investment price.

The remainder of the paper is as follows. In the next section I use the neoclassical growth model to derive the identification assumptions at the heart of the analysis and show how they can be used to identify the affects of technology shocks. After this I discuss the data used in the analysis, present the main empirical findings and evaluate the robustness of these findings. Finally, I summarize and suggest directions for future research.

2. Empirical Framework

In this section I describe how the identifying assumptions exploited in the empirical analysis can be derived from a neoclassical growth model. The first sub-section describes the economic model. This model is deliberately stripped down to make the discussion as transparent as possible. The second sub-section describes how the identifying assumptions derived from the model can be implemented econometrically. The econometric strategy is consistent with a broad class of models which share the same balanced growth properties as the model considered here.

2.1. Economic Model

The model is adapted from the competitive equilibrium growth model of Greenwood, *et. al.* (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

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

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

and

$$\begin{aligned} A_t &= \exp(\gamma + C_a(L)\varepsilon_{at})A_{t-1}, \gamma \geq 0 \\ V_t &= \exp(\nu + C_v(L)\varepsilon_{vt})V_{t-1}, \nu \geq 0 \\ [\varepsilon_{at}, \varepsilon_{vt}]' &\sim N(0, D),\ D \text{ diagonal} \end{aligned} \tag{4}$$

Here $\mathcal{E}_0$ is the expectations operator conditional on time $t = 0$ information, $U(\cdot, \cdot)$ is a utility function 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 $C_a(L)$ and $C_v(L)$ are square summable polynomials in the lag operator L.

The differences with Greenwood, *et. al.* (1997) are (i) there is only one capital good and (ii) exogenous technology has a stochastic instead of a deterministic trend. The first difference is not crucial to the argument. Difference (ii) is substantial because it is the reason why technology shocks have permanent effects in this model. Many real business cycle models assume a stochastic trend in technology, but much of the emphasis in this research is on persistent, but transitory technology shocks. The econometric identification used below, which follows the standard methodology, does not consider transitory technology shocks.

Galí (1999) argues that the stochastic trend assumption is natural when thinking about purely technological disturbances. More substantially Alvarez and Jermann (2002) present compelling evidence that without a unit root, it is difficult to resolve data on asset prices with economic theory. Yet, a plausible interpretation regarding the neutral term is that it represents "productivity" shocks, disturbances to production possibilities more generally conceived and not necessarily due to technological change, such as taxes, regulation and market structure. These disturbances may very well be transitory. By ignoring transitory effects I am presenting a lower bound on the contribution to business cycles of technology shocks more generally conceived.

The long run implications of the model are found by considering its balanced growth properties. The balanced growth path is derived from the unique transformation of the endogenous variables which renders them stationary. It is straightforward to confirm that along a balanced growth path the following variables are stationary:

$$Y_t/Z_t \quad C_t/Z_t, \quad X_t/Z_t, \quad K_{t+1}/(Z_t V_t), \quad (Y_t/H_t)/Z_t \quad \text{and } H_t, \tag{5}$$

where $Y_t = C_t + X_t$ and $Z_t = A_t^{1/(1-\alpha)} V_t^{\alpha/(1-\alpha)}$. Therefore, along a balanced growth path, output, consumption, investment and labor productivity (all measured in consumption units) on average each grow at the rate $(\gamma + \alpha\nu)/(1-\alpha)$. In addition, the capital stock grows at the rate $(\gamma + \nu)/(1-\alpha)$, and hours worked is stationary.

From (5) it is immediate that a positive innovation to neutral or investment-specific technology leads to permanent increases in output, consumption, investment, the capital stock, and labor productivity, but has no effect on hours worked in the long run. Most important for what follows is the fact that both sources of technological change influence labor productivity in the long run. That is, at any time t

$$\lim_{j\to\infty}\frac{\partial \ln Y_{t+j}/H_{t+j}}{\partial \varepsilon_{vt}}=\frac{\alpha}{1-\alpha}>0 \text{ and } \lim_{j\to\infty}\frac{\partial \ln Y_{t+j}/H_{t+j}}{\partial \varepsilon_{at}}=\frac{1}{1-\alpha}>0. \tag{6}$$

This is different from a model without investment-specific technological change or if investment-specific shocks are stationary about a deterministic trend, because in such a model only neutral technological change influences labor productivity in the long run.

Notice from (2) and (3) that the number of consumption units that must be given up to get an additional unit of capital is $1/V_t$. That is, in the competitive equilibrium of this economy, the real price of investment, P_t, is $1/V_t$. Obviously, the only shock in this economy that has a permanent effect on P_t is an innovation to V_t. Neutral technological change has no impact on the technical rate of transformation between consumption goods and investment goods and therefore on the real price of investment. Mathematically,

$$\lim_{j\to\infty}\frac{\partial \ln P_{t+j}}{\partial \varepsilon_{vt}}=-1<0 \text{ and } \lim_{j\to\infty}\frac{\partial \ln P_{t+j}}{\partial \varepsilon_{at}}=0. \tag{7}$$

The simple growth model implies that the real investment price is completely determined by the level of investment-specific technology. In a more general (and realistic) model with curvature in the transformation frontier of producing investment and consumption goods, for example the two-sector model studied by Boldrin, Christiano and Fisher (2001), this would not be true. However, such a model, if it is consistent with balanced growth, would continue to have the property that the only factor influencing the real price in the long run would be investment-specific technological change.[2]

It is straightforward to extend the simple growth model in other ways to incorporate many alternative propagation mechanisms, including models with money and sticky prices and

[2] Greenwood, *et. al.* (1997) consider and reject several alternative mechanisms which in principle might account for the secular trend in the real investment price instead of investment-specific technological change. One important example they consider is different factor shares for the investment and consumption good sectors in a two-sector model. If these shares are of the right magnitude then there could be a secular trend in the real price without one in investment-specific technology. Greenwood, *et. al.* (1997) argued that this hypothesis requires assuming implausible parameter values.

wages. These models can also have other exogenous shocks, as long as they have transitory effects only. That is as long as,

$$\lim_{j \to \infty} \frac{\partial \ln Y_{t+j}/H_{t+j}}{\partial \varepsilon_{xt}} = 0 \text{ and } \lim_{j \to \infty} \frac{\partial \ln P_{t+j}}{\partial \varepsilon_{xt}} = 0, \tag{8}$$

for all other shocks x. In these alternative models there may be other endogenous variables, but the balanced growth properties given in (5) will be the same, as long as technological change is neutral and investment-specific.

At this stage of the analysis one could specify a parameterized theoretical model which matched several interesting unconditional moments in the data and use this model to assess the contribution of technology shocks to the business cycle. The earliest paper to do this with investment-specific shocks was Greenwood, Hercowitz and Huffman (1988). Other papers which have considered the business cycle implications of investment-specific shocks are Campbell (1998), Christiano and Fisher (1998), Fisher (1997), and Greenwood, Hercowitz and Krusell (2000). As we have learned from the literature on neutral technology shocks, the contribution of technology shocks to the business cycle derived from quantitative business cycle models may not correspond with that derived from an econometric analysis which takes a weaker stand on the nature of the propagation mechanism. This helps to motivate using the method described in the next section to identify the importance of technology shocks for the business cycle.

2.2. Econometric Strategy

Two basic assumptions summarize the class of models for which (6)-(8) hold. In words, these assumptions are:

Assumption A1. Only shocks to exogenous investment-specific technology affect the real investment price in the long run;

Assumption A2. Only shocks to exogenous neutral or investment-specific technology affect labor productivity in the long run.

In addition to these assumptions, I define a "shock" to be a statistically independent innovation. I now describe how these assumptions can be used to identify the dynamic responses of variables to exogenous neutral and investment-specific technology shocks within the standard econometric framework.

The econometric identification strategy in which I incorporate A1 and A2 is a simple adaptation of Shapiro and Watson (1988).[3] To begin, the equilibrium of the economic model (and its admissible generalizations) has a moving average representation,

$$y_t = \Phi(L)\varepsilon_t \tag{9}$$

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

Under the assumption that $\Phi(L)$ is invertible (typically the case in real business cycle models) we may recover the exogenous shocks ε_{vt} and ε_{at} with two instrumental variables (IV) regressions. First, consider

$$\Delta p_t = \Gamma_{pp}(L)\Delta p_{t-1} + \Gamma_{pa}(L)\Delta a_t + \Gamma_{ph}(L)h_t + \Gamma_{pq}(L)q_t + \varepsilon_{vt}, \tag{10}$$

where the $\Gamma_{xy}(L)$'s here and below are lag polynomials derived by inverting $\Phi(L)$. This equation relates changes in the real investment price to current and lagged values of the endogenous variables. The contemporaneous effects of all non-ε_{vt} shocks effect the current Δp_t through Δa_t, h_t and q_t. By assumption A1, it follows that the long run multipliers from

[3] See Basu and Fernald (1998) for a different identification strategy which does not rely on long run restrictions. At this stage it is unclear what the implications of investment-specific technological change are for their approach.

these variables to the real price are zero. Imposing this restriction is the same as imposing a unit root in each of the lag polynomials associated with Δa_t, h_t and q_t. That is,

$$\Gamma_{pj}(L) = \tilde{\Gamma}_{pj}(L)(1-L),\ \ j = a, h, q\ \ .$$

As long as $\tilde{\Gamma}_{pj}(1) \neq 0,\ \ j = a, h, q$, it follows under assumption A1 that (10) becomes

$$\Delta p_t = \Gamma_{pp}(L)\Delta p_{t-1} + \tilde{\Gamma}_{pa}(L)\Delta^2 a_t + \tilde{\Gamma}_{ph}(L)\Delta h_t + \tilde{\Gamma}_{pq}(L)\Delta q_t + \varepsilon_{vt}. \tag{11}$$

Innovations to the real investment price may affect the contemporaneous values of Δa_t, h_t and q_t. Consequently this equation cannot be estimated by ordinary least squares. However, given that ε_{vt} is exogenous, this shock is orthogonal to all variables dated $t-1$ and earlier. Hence we can estimate (11) by IV, using lagged values of y_t as instruments. The residuals of this estimation are my estimates of ε_{vt}, $\hat{\varepsilon}_{vt}$.[4]

The equation used to identify the neutral shock is

$$\Delta a_t = \Gamma_{ap}(L)\Delta p_{t-1} + \Gamma_{aa}(L)\Delta a_{t-1} + \Gamma_{ah}(L)h_t + \Gamma_{aq}(L)q_t + \theta\varepsilon_{vt} + \varepsilon_{at}. \tag{12}$$

Here contemporaneous non-ε_{at} shocks influence Δa_t indirectly through h_t, q_t and directly through ε_{vt}. By a similar argument to before, assumption A2 implies the long run multipliers from h_t and q_t to Δa_t are zero, but that the long run multiplier from ε_{vt} is non-zero. When these assumptions are incorporated into (12),

$$\Delta a_t = \Gamma_{ap}(L)\Delta p_{t-1} + \Gamma_{aa}(L)\Delta a_{t-1} + \tilde{\Gamma}_{ah}(L)\Delta h_t + \tilde{\Gamma}_{pq}(L)\Delta q_t + \theta\varepsilon_{vt} + \varepsilon_{at}. \tag{13}$$

Notice that (13) implies ε_{vt} can have a long run impact on the level of a_t if neutral technological change has a long run impact. Similar to (11) this equation can be estimated by IV using lagged values of y_t as instruments. The residuals from (13), $\hat{\varepsilon}_{at}$ are my estimates

[4]Notice that the identification of the investment-specific shock does not rely on the orthogonality of this shock with the contemporaneous neutral shock.

of ε_{at}. Including $\hat{\varepsilon}_{vt}$ in (13) ensures $\hat{\varepsilon}_{at}$ is orthogonal to the investment-specific shock within the sample period.

These steps for estimating the neutral shock differ from the existing literature because the real price and the investment-specific shock are included in (13). This difference is entirely due to the difference of assumption A2 from the usual identifying assumption that only neutral technological change has a long run impact on labor productivity. By omitting Δp_{t-1} and ε_{vt} from (13), estimates of the coefficients on Δa_{t-1}, Δh_t and Δq_t are likely biased. The ultimate impact of this bias on the estimates of ε_{at} and estimated dynamic responses of variables to this shock is unclear at this stage. However, even if previous estimates of ε_{at} are valid and therefore the finding that these shocks are unimportant for the business cycle is correct, there is still scope for technology shocks to impact the business cycle through ε_{vt}.

Estimating (11) and (13) by IV yields estimates of the shocks, $\hat{\varepsilon}_{vt}$ and $\hat{\varepsilon}_{at}$. I am interested in identifying the dynamic responses of the variables in y_t to each shock and decomposing the sample path of any element of y_t into parts due to the two shocks. This is done efficiently by estimating the reduced form vector-autoregression,

$$y_t = A(L)y_{t-1} + u_t, \mathcal{E}_0 u_t u_t' = \Sigma, \tag{14}$$

where $A(L)$ is a square-summable matrix lag polynomial. The reduced form residuals are linearly related to the fundamental shocks ε_t in the linear approximation to a given real business cycle model through a matrix B,

$$u_t = B\varepsilon_t, BB' = \Sigma.$$

The first two elements of ε_t are $\hat{\varepsilon}_{vt}$ and $\hat{\varepsilon}_{at}$. Therefore, to derive the dynamic responses of interest we need only estimate the first two columns of B. Since the first two elements of ε_t are orthogonal to the other elements in the vector we can do this by applying ordinary least squares to the n equations with each residual from (14) on the left hand side of the equation and the two estimated shocks on the right hand side. Finally, to derive the response of any variable in y_t to either of the two technology shocks we can simulate (14) using the appropriate elements of B. We can also use these estimates to decompose the sample path of any variable in y_t into parts due to the two identified shocks.[5]

3. The Data

This section describes the data used in the empirical analysis. I begin by describing the real investment price data, which is a crucial input into the empirical analysis. After this I discuss the specific variables included in the application of the econometric model to US data.

3.1. The Real Price of Investment

As is standard, I measure the real price of investment as the ratio of a suitably chosen investment deflator and a deflator for consumption derived from the National Income and Product Accounts (NIPA). The consumption deflator I use corresponds to nondurable and service consumption, the service flow from consumer durables and government consumption. The NIPA investment deflators are well-known to be poorly measured, so finding a suitable investment deflator is the main challenge to constructing a real investment price. In this subsection I describe the choices underlying my chosen deflator and then I describe the resulting real price.

Poor measurement is one reason why the importance of investment-specific technological

[5]This procedure yields identical results to the following adaptation of the methodology in Blanchard and Quah (1989), as long as the number of lags in (10) and (12) are identical to the lags in (14). The long run effects of the system (14) are summarized by

$$y_t = [I - A(1)]^{-1} B\varepsilon_t = \Phi(1)B\varepsilon_t.$$

The preceding discussion implies that the first two rows of $\Phi(1)B$ have zeros everywhere except in the first element of the first row and first two elements of the second row. It follows that to estimate B we can follow four simple steps. First, estimate the unconstrained vector-autoregression (14). Second, use the estimated coefficients to compute $A(1)$. Third, compute the lower triangular Choleski matrix, C, so that $CC' = \Phi(1)\Sigma\Phi(1)'$. Fourth, use the fact that $\Phi(1)B$ is a factor of $\Phi(1)^{-1}\Sigma\Phi(1)^{-1\prime}$ to solve for $B = \Phi(1)^{-1}C$. Using the first two columns of B one can compute the dynamic response functions and historical decompositions of interest.

change has taken so long to be recognized. Gordon (1989) argued forcefully that the NIPA producer durable equipment deflator was seriously miss-measured because of its treatment of quality change. Through exhaustive use of primary sources he formulated a quality adjusted deflator. However, it was not until Greenwood, *et. al.* (1997) that the full import of these adjustments were recognized. They showed that the real price of producer durable equipment derived using Gordon's deflator has a pronounced downward secular trend. Based on a model similar to the one in section 2.1 they showed that the technological change implied by this trend accounts for about 58 percent of output growth between 1954 and 1990.

To arrive at their estimates Greenwood, *et. al.* (1997) extended Gordon's original sample, which ends in 1983, with a rough bias adjustment to the NIPA data. Cummins and Violante (2002) derived a more systematic update of the Gordon data. They estimated econometric models of the bias adjustment implicit in the individual deflators underlying Gordon's equipment deflator and used these models to bias adjust the NIPA data for the period 1984-2000. Their findings confirm the Greenwood, *et. al.* (1997) result that investment-specific technological change is a major source of growth.

I initially consider two investment deflators based on the Gordon-Cummins-Violante (GCV) equipment deflator. The first measure is "equipment" and is derived directly from the GCV equipment deflator. The second is "total investment" which is a broader measure but still includes the GCV deflator along with other NIPA deflators. This is designed to correspond to the investment measures typically used in real business cycle studies.

To be used in the econometric analysis, these deflators need to be quarterly series. Since the GCV series is an annual series it must be interpolated. There is no generally agreed on method of interpolation. Here I use the popular approach due to Denton (1971). As shown by Fernandez (1981), this method fits within the generalized least squares interpolation-by-related-series class of interpolation schemes introduced by Chow and Lin (1971). Interpolation-by-related-series uses information in a higher frequency indicator variable to interpolate a better quality but lower frequency variable. Denton's version of this method minimizes 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.[6]

My 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. My total investment deflator is derived by using the appropriate chain-weighting formula to combine my equipment-specific deflator with NIPA based deflators for non-residential structures, residential structures, consumer durables, and government investment.[7] The Denton method retains the low frequency information in the higher quality series and so any error in the interpolation underlying these deflators should have little consequence for the identification of the technology shocks, which relies on the low frequency part of the data.

Figure 1 displays the two investment deflators and the associated real investment prices, along with series based only on the NIPA accounts for the sample period 1955:I-2000:IV.[8] In each plot the solid line corresponds to the GCV based measure and the dashed line corresponds to the NIPA measures, both in logs. This figure is helpful for making three basic points. First, the quality bias in the NIPA deflators is large making them unsuitable for constructing real prices. Second, consistent with Cummins and Violante (2002) and Greenwood, *et. al.* (1997), equipment-specific technological change has been substantial since 1955. The data indicate a 200 percent drop in the real equipment price. Third, the

[6] Denton's method is used by the IMF in their official statistics. When the related series is a good indicator the practical differences among the available methods are small. An extensive discussion of alternative interpolation methods can be found in *Handbook of Quarterly National Accounts Compliation.* This can be currently viewed at `www.imf.org/external/pubs/ft/qna/2000/Textbook/index.htm`

[7] Gordon estimates an annual quality adjusted consumer durables deflator which also indicates considerable quality bias in the corresponding NIPA deflator. For the consumer durable deflator used to construct the total investment deflator I interpolate the annual Gordon consumer durable deflator using the NIPA deflator as the related series for the period 1947-1983 and splice this to the NIPA deflator for the remaining years of my sample.

[8] I exclude data before 1955 for three main reasons. First, it is common in the real business cycle literature to focus on the post-Korean war era (see for example, Prescott 1986). Second, I am more concerned about the quality of my interpolations before 1955 because I believe the quality bias in the NIPA data may be stronger than later in the sample. Third, estimates of the magnitude of the impact of neutral technology shocks on the business cycle appear to be sensitive to including variables associated with monetary policy. For empirical studies associated with US monetary policy it is customary to select dates for the beginning of the sample period of analysis that are several years after the Treasury Accord of 1951.

real total investment price declines by much less, but still has a secular trend. The weaker trend in this price may be due to a slower rate of quality change in non-equipment investment or it may be due to the fact that the deflators for these investment goods have not been quality adjusted.[9]

It is useful to briefly consider why the dynamics of the real price and quantity data strongly suggests investment-specific technological change is important for understanding both business cycles and growth, even prior to any econometric analysis. Figure 2 shows the long run and short run association between real investment prices and quantities (similar figures appear in Greenwood, *et. al.* 1997). The left column reproduces the GCV based real prices from figure 1 along with ratios of the quantity of investment to output with the latter in consumption units. These plots show that the real price declines coincide with large increases in the relative quantity of investment goods produced, illustrating the importance of investment-specific technological change for capital accumulation and hence growth.

The derivation in section 2.1 is based on the balanced growth hypothesis. The consistency of the two investment series for this hypothesis can be assessed by observing that the sum of the real price and real share series must be stationary under balanced growth. By this test equipment is not a good measure of the object called investment in the growth model, because the sum of the two series in the top left column has an upward trend. The presence of this trend can be rendered consistent with a neoclassical growth model if we extend the notion of balanced growth as in Kongsamut, Rebelo and Xie (2001). Notice that while the evidence on equipment investment is inconsistent with the growth model as written down in section 2.1, total investment is consistent, since the sum of the two series in the lower left column is stationary.

The right column displays the business cycle components of real investment prices and quantities. These plots confirm the observation of Greenwood, *et. al.* (1997, 2000) that, even in the short run, investment-specific supply shocks seem to be closely related to investment.

[9]Gort, Greenwood, and Rupert (1999) estimate significant quality bias in the NIPA deflators for non-residential structures.

In figure 2, the business cycle components are derived using the Baxter and King (1999) band-pass filter which excludes frequencies higher than one and a half years and frequencies lower than eight years.[10] The top right plot shows a negative relationship between the investment prices and quantities, strongly suggesting a role for cost-reducing technology shocks. This negative relationship is apparent throughout the sample. The unconditional correlation is -0.67. The relationship with total investment is not as strong (the correlation is -0.41). Some of the difference may be due to measurement error, but the likelihood that residential investment has a strong "demand"-driven component probably plays a role as well. Still, overall the data suggest that investment-specific technology shocks play a key role in the business cycle.

3.2. Variables in the Econometric Application

Figure 3 displays the variables underlying the main results presented in the next section. Implementing the econometric model in section 2.2 requires only the growth rate of the real investment price, the growth rate of average labor productivity, and per capita hours worked. The variables used to measure these objects are plotted in the left column of figure 3. The equipment price is my measure of the real price because it is presumed to be more precisely measured than the total investment price.[11] Results based on the total investment price are similar. Labor productivity is the non-farm business measure published by the Bureau of Labor Statistics (BLS). Per capita hours (in logs) is the BLS hours worked (not hours paid) measure corresponding to the productivity measure, divided by the working age population. To retain consistency with the growth model I express labor productivity in consumption units per hour using my consumption deflator. The first two variables, real price growth and productivity growth are clearly stationary. However, the stationarity of per capita hours is

[10] To implement the Baxter and King filter I must select the number of lags (leads) in the filter. I use their suggested value of 12 quarters.

[11] The sharp changes in the real equipment price in 1973-74 are an artifact of the impact of the Nixon wage and price controls on the construction of the equipment deflator (see Cummins and Violante 2002). Since this is a transitory phenomenon it should not affect the identification of the investment-specific technology shocks.

a matter of controversy in the literature and so some discussion of this is necessary.

Francis and Ramey (2001) argue that, since standard tests of the null hypothesis of a unit root (e.g. Perron and Phillips 1988) in per capita hours are not rejected, per capita hours should be first differenced prior to the analysis. Consistent with Francis and Ramey (2001), tests of a unit root in per capita hours as plotted in figure 3 are not rejected at conventional significance levels. Of course non-rejection of a null hypothesis does not mean the alternative hypothesis, in this case level stationarity, is rejected. Indeed, the Kwiatkowski, Phillips, Schmidt and Shin (1992) test of the null of level stationarity against the alternative of a unit root is not rejected for this series at conventional significance levels either.[12] Therefore, as in Christiano, *et. al.* (2002), neither level nor difference stationarity of per capita hours can be rejected by classical statistical criteria. Christiano, *et. al.* (2002) use Bayesian methods to argue that the preponderance of the evidence points toward level stationarity as the most plausible assumption.[13] Finally, the purpose of this paper is to examine the technology-driven business cycle hypothesis and standard versions of this hypothesis imply per capita hours are level stationary. These considerations suggest it is reasonable to work with per capita hours in levels. I discuss alternative ways of incorporating per capita hours into the analysis below.

In addition to considering the minimal set of variables needed for identification, Galí (1999) and Christiano, *et. al.* (2002) also consider adding variables to assess the robustness

[12] Kwiatkowski, *et. al.* (1992) demonstrate that the asymptotic critical values of their test imply over rejection of the null when the data is autocorrelated. For example, in their Table 2, p. 171 if the true data generating process is an AR(1) with autoregressive coefficient of 0.8 then the true size of a test with nominal size of 5% is between 24% and 30%, depending on the sample size. Therefore, following Christiano, *et. al.* (2002), I base my conclusions regarding level stationarity on small sample critical values derived using Monte Carlo methods. I assumed the data generating mechanism was an AR(1), used 10,000 Monte Carlo draws of sample sizes of length 188, and used the recommended lag truncation parameter (8) for the test. The 5 percent critical values for autocorrelation coefficients 0.85, 0.9 and 0.95 are 0.85, 1.03 and 1.40, respectively. The corresponding test statistic for per capita hours worked is 0.47. Test statistics exceeding the critical values lead to rejection of the null of level stationarity. Therefore the test is not rejected at the 5% significance level. Note that the asymptotic 5% critical value from Table 1, p. 166 of Kwiatkowski, *et. al.* (1992) is 0.46.

[13] The debate over level versus difference stationarity is controversial because, as Christiano, *et. al.* (2002) show, the sign of the estimated response of hours to a neutral technology shock depends on which is assumed. Galí's (1999) finding that neutral technology shocks are irrelevant to the business cycle is not sensitive to the level versus difference stationarity choice.

of their findings. Christiano, *et. al.* (2002) argue that the contribution to business cycles of neutral technological change may be overstated by excluding certain key variables. Motivated by their findings, I include the four variables plotted in the right column in the analysis as well. As in that paper inflation is measured by the GDP deflator and the nominal interest rate is the 3-month Treasury Bill rate. I also include the nominal ratios of consumption and investment to output, in logs. These variables are suggested by the balanced growth implications of the growth model and may be important for correctly identifying technology shocks.

To retain consistency with the measure of labor productivity I use, my nominal output measure is the corresponding BLS output measure. I use the consumption measure corresponding to the consumption deflator used to deflate the nominal equipment price. The investment measure is total investment as defined above. As in the case of the three variables in the left column, one cannot reject the hypothesis of level stationarity using the test of Kwiatkowski, *et. al.* (1992) for any of the four variables in the right column.[14]

4. Main Findings

The standard one-technology-shock identification scheme can be implemented with just two variables, productivity growth and hours. The two-technology-shock identification scheme proposed in this paper can be implemented with just three variables, productivity growth, hours and real investment price growth. In the first sub-section I describe my findings for these minimal systems using the real equipment price as the measure of the real investment price. In the second subsection I describe my findings for larger models which add variables to the minimal systems. Regardless of the size of the empirical models estimated, the results strongly suggest an important role for technology shocks in the business cycle with the largest

[14] See footnote 12 for details of how I conducted these tests. In addition to implying the nominal expenditure shares are stationary, the growth model implies the real price, labor productivity, consumption and investment are integrated of order 1. Standard tests do not reject this hypothesis for each of these variables at standard levels of significance. Tests of the null hypothesis of trend stationarity are strongly rejected for the price but not the other variables.

contribution coming from investment-specific technology shocks.

4.1. Models with a Minimal Number of Variables

I estimated the minimal systems using four lags, which is consistent with the literature. The complete estimated dynamic responses (out to 64 quarters) of the inverse real investment price ($1/P$), labor productivity (Y/H), hours (H) and output (Y) are displayed in figure 4. The responses to investment-specific shocks are labelled "I-Shock Responses" and the responses to neutral shocks are labelled "N-Shock Responses." I use "one-shock model" to describe the econometric model estimated under the one-technology-shock hypothesis and "two-shock model" to describe the model estimated under the two-technology-shock hypothesis. All responses are to one-standard deviation positive innovations to technology and are plotted relative to the standard deviation of the shock.

Consider the N-shock responses in the one-shock model in the right-most plot. The permanent and positive response of labor productivity was used to identify these responses and the other responses are conditional on this outcome. With hours included in the model in levels, hours responds positively about a quarter of a percent before declining slowly back to zero. This dynamic response is consistent with the one reported recently by Christiano, *et. al.* (2002) who include hours in the same way. Given the similarity of the productivity responses as well, the response of output (the sum of labor-productivity and hours) is also consistent with this other work.

Now consider the N-shock responses estimated using the two-shock model, in the middle plot. The responses of productivity, hours and output are strikingly similar to the one-shock model. The main difference is that the response of hours, and therefore also output, is dampened slightly in the two-shock model. Including real investment price growth in the one-shock model has little effect on the estimated responses of the one-shock model (not shown).[15] It follows that the two identification strategies are essentially identifying the

[15] This finding suggests the real equipment price does not add much new information for forecasting productivity that is not already contained in productivity and hours.

same shock. The two-shock identification has the advantage of yielding the response of the (inverse) equipment price to an N-shock. Interestingly the equipment price rises (its inverse falls) after a positive N-shock. This is consistent with the predictions of real business cycle models with a rising short-run supply price of capital, such as in the two-sector model in Christiano and Fisher (1998). This latter finding adds support to the interpretation of the N-shock responses as being genuine neutral technology shocks.

The I-shock responses in the left-most plot are conditional on the permanent and (positive) negative response of the (inverse) real equipment price. The peak response of hours is a little more than one percent. This is four times greater than in the hours response to an N-shock in the same model. The positive response of hours to an I-shock is consistent with the real business cycle models studied by Christiano and Fisher (1998) and Greenwood, Hercowitz and Krusell (2000). After an initial increase, the response of productivity declines below zero before rising to it long run positive value. Note that while theory predicts the productivity response to be positive in the long run, this is not imposed on the estimation. The initial decline in productivity is also reasonable from the perspective of theory. This is because investment takes time to have an impact on the capital stock and so productivity can be driven by hours in the aftermath of an I-shock if hours worked responds strongly. Given the relatively small movements in productivity, output responds similarly to hours. Output's response to an I-shock is similar to that for an N-shock in the short run, but it declines more rapidly and converges to a lower long run value.

One's confidence in the interpretation of the identified shocks depends in part on whether theory can explain the dynamic responses to them. It is also important to assess the degree of sampling uncertainty in the estimates. Information about this is presented in figure 5 which displays the responses of hours, productivity and the equipment price to the identified shocks over a shorter horizon (32 quarters) and with equal-tailed, point-by-point 95 percent confidence bands (dashed lines).[16] Several points are worth noting here. First, the hours

[16] These bands are computed using a standard bootstrap procedure combined with the Hall (1992) method of constructing confidence intervals. See Killian (1999) for a discussion of bootstrap confidence intervals in a relevant context. He finds that Hall's confidence interval has relatively good classical coverage probabilities

responses to neutral shocks in both models are not significantly different from zero, but the response to an I-shock is significant. Second, the increase in the equipment price following an N-shock in the two-shock model is significant, at lease in the first few periods after a shock. Third, the productivity response to an I-shock is not statistically significant.

The dynamic responses of hours worked are broadly consistent with theory, but are they of the kind which can account for observed hours? The weak responses of hours to N-shocks suggests these technology shocks are unimportant for this variable. On the other hand, the strong and statistically significant responses to an I-shock suggests these shocks are important. This can be assessed by examining figure 6 which shows historical decompositions of hours due to investment-specific, neutral and both technology shocks along with the actual path of hours.[17] The first row shows the investment-specific shock accounts for a large part of the variation in hours worked, particularly around recessions. In striking contrast, neutral technology shocks seem almost unrelated to the business cycle (the decomposition for the one-shock model, not shown, is similar). The combined effects of the two shocks track actual hours quite closely.

Although it seems clear from figure 6 that the investment-specific technology-shocks account for a large part of the business cycle and neutral shocks account for much less, hours worked has some high and low frequency variation which may confound the interpretation of such a figure. I now assess the contributions of the identified technology shocks to business cycles more precisely using figure 7 and table 1. The figure shows plots of the business cycle component of actual hours (solid lines) and hours as predicted by the empirical models (dashed lines) where the business cycle components have been calculated using the same

compared to other bootstrap confidence intervals. To the extent that a point estimate lies closer to the lower (upper) bound of the confidence interval then this is indicative of downward (upward) bias in the point estimates. In figure 5 and below there is evidence of bias in the point estimates. This appears to be due to non-linearity in the mapping from the regression coefficients to the dynamic response functions, and not due to biased coefficient estimates. Consequently I do not employ the Killian (1998) "bias-correction" here. A Baysesian analysis of the liklihood of different responses, as suggested by Sims and Zha (1999), is left to future research.

[17] The predicted time path of hours for a given model and shock is based on simulating the estimated vector-autoregression underlying the dynamic responses in figures 4 and 5 using the estimated shocks and the actual data in the first four periods of the sample to initialize the simulation.

procedure as in figure 2. The table shows summary statistics useful for quantifying the extent to which technology shocks account for business cycle dynamics. The table includes evidence for both hours and output and also a case (right-most column) where the one-shock model is appended to include the linearly detrended real equipment price. This latter case is discussed below.

The business cycle dynamics of hours worked derived from the N-shocks in the two models is displayed in the lower row of figure 8, with the two-shock model on the left. Consistent with the dynamic responses of hours shown in figures 4 and 5, the path of hours is similar across the two identifications. In both cases, the variation in hours seems small, and the predicted path does not seem to co-move strongly with actual hours. This is consistent with Galí (1999) and Christiano, *et. al.* (2002) who have shown N-shocks to be unimportant for the business cycle. In contrast, the I-shock in the minimal two-shock model seems to generate volatility in hours near that of actual hours and there seems to be much closer conformity with actual hours than for N-shocks. The overall effect of technology shocks is to generate fluctuations in hours worked that are quite close to actual hours. If anything, technology shocks seem to account for too much of the variation in hours. For example, the recession in the early 1980s is widely believed to have been due in large part to monetary policy, but here the recession is attributed almost entirely to I-shocks.

The sense of I-shocks generating a significant fraction of business cycle variation in hours worked is confirmed by the findings reported in table 1. Panel A of this table shows the relative volatility of the technology components of the two models, $\sigma^2_{H^m}/\sigma^2_{H^d}$, and the correlation of these variables with actual hours, $\rho(H^m, H^d)$. The numbers in parenthesis are nominal equal-tailed 95 percent confidence intervals. The nominal confidence intervals for the variance ratios sometimes include inadmissible values for this statistic (less than zero or greater than 1). In these cases the bound of the interval is set to the nearest admissible value for the statistic.

Consider the two-shock model first. Consistent with figure 7 investment–specific shocks generate 54 percent of the business cycle volatility of hours and we have more than 95 percent confidence that this percentage exceeds 20. Furthermore the correlation coefficient is large, 0.79, and statistically significant. These results strongly suggest a major role for investment-specific shocks in generating the business cycle. On the other hand, the impact of neutral shocks in the two-shock model is similar to the one-shock model, that is small. The confidence intervals suggest that it is unlikely that these shocks generate more than 8 percent of the hours worked variation of interest and are relatively weakly correlated with actual hours. Finally, consistent with the strong impact of investment-specific shocks, the combined effect of the technology shocks in the two-shock model is strikingly large and highly correlated with actual hours.[18]

Panel B of table 1 shows similar statistics for output, including the variance ratio $\sigma^2_{Y^m}/\sigma^2_{Y^d}$ and the correlation $\rho(Y^m, Y^d)$. These confirm the impression that investment-specific shocks are important for the business cycle. Consistent with the pattern of responses of productivity to neutral shocks, these shocks are more important for explaining output. Still, the investment–specific shocks are the most important of the two technology shocks.

4.2. Larger Models

We now consider the findings based on estimating the larger systems. As discussed in section 3.2, these systems consist of the variables in the minimal models plus the nominal ratios of investment to output, consumption to output, inflation and a short-term nominal interest rate. Figure 8 displays the complete dynamic responses for the same variables considered above in the top row and consumption (C), investment (X) and the ex post real interest rate (R) in the bottom row. To facilitate comparisons across the two identification schemes, investment is plotted in consumption units for the N-shock cases. Investment is in units of equipment in the I-shock case.

The N-shock responses in the right two columns are similar in magnitude to the compa-

[18]The total contribution of technology shocks would be exactly equal to the sum of the contributions of the two shocks if the estimated shocks were exactly orthogonal to the each other at all leads and lags. The estimation procedure only guarantees that the two shocks are orthogonal contemporaneously. In practice there are slight correlations at various leads and lags of the shocks. Differences between the sum of the contributions and entries in the first column of table 1 (and table 2, below) reflect these slight correlations.

rable responses in figure 4. The main difference is that output and hours rise more slowly to their peaks and that output, hours and productivity all take longer to attain their long run values. In the two-shock case, the response of the equipment price is somewhat stronger than with the corresponding minimal system, but qualitatively quite similar. In the larger systems we can assess the plausibility of the identification schemes in terms of the responses of consumption, investment and the real interest rate. Given the positive long run responses of consumption and investment and the rise in the real interest rate, these responses are broadly consistent with neoclassical theory. Finally, as with the minimal systems the two identification strategies seem to be identifying the same neutral shock.

Including the additional variables has more of an impact on the responses to I-shocks. The responses that are comparable to those in figure 4 are displayed in the top plot of the left-most column. First, the initial response of the inverse equipment price is weaker - the initial peak of the price response in figure 4 is nearly 1.5 percent, while here the response is about half as large as that. However, the inverse price converges to a larger positive value here (3 percent versus 1.8 percent). The initial response of hours is also somewhat smaller than before (0.8 percent versus 1.1 percent before). More interestingly there is now a second hump in the hours response. As with the comparable minimal system, the overall response of hours is much stronger than in the N-shock case. Productivity is much more persistent in its negative response compared to the minimal case. Now it takes over 150 quarters for the productivity response to turn positive compare to about 20 before (not shown). The behavior of productivity means that, after an initial burst, output declines, before turning positive.[19]

Now consider the responses in the lower left-most plot. Notice that investment initially rises quite strongly, then declines just as strongly, before sustained growth toward the new long run level sets in. This response seems to correspond quite closely to the hours response. In particular, the initial rise and fall of hours coincides with the boom and decline in invest-

[19]Recall that output is measured in consumption units. If it were measured in "output units," that is using a chain-weighting formula that accomodated changes in the consumption and investment deflators, then the response would be mostly positive.

ment, while the second hump in hours coincides with the resumption of positive investment growth. Consumption's response seems quite weak. However, while not clear from the figure, it does converge to a positive value. Campbell (1998) describes an investment-specific shock driven vintage capital model which generates similar responses to these. Finally, the real interest rate response is quite similar to the N-shock case. In sum, while somewhat different from the responses estimated in the minimal two-shock system, the I-shock responses in the larger two-shock model are broadly consistent with each other and with theory.

Some indication of the sampling uncertainty underlying the responses in figure 8 are shown in figures 9 and 10. Several observations are worth making here. First, as in the minimal case, the response of hours to an I-shock is significant. Interestingly, the responses of hours in the N-shock cases are significant after several quarters when in the minimal systems they were not. Second, the positive response of the equipment price to an N-shock continues to be significant. Finally, the responses of consumption, investment, output and the real interest rate in figure 10 are significant for at least a couple of quarters.

We now consider how important the identified technology shocks are for the business cycle in the larger systems. Figures 11 and 12 table 2, the analogues of figures 6 and 7 and table 1, confirm the main findings from the minimal systems. Figure 11 is somewhat different from figure 6, with investment-specific hours less closely tracking actual hours and hours due to neutral shocks more obviously cyclical. Still, the combined effect of the shocks seems large and investment-specific shocks seem much more important. One notable difference with the minimal system is that here there seems more room for monetary policy during the Paul Volker period. This impression is confirmed in figure 12 where neutral shocks still seem to be little related to the business cycle dynamics of hours, while investment-specific shocks seem to be a major part of these dynamics. As before, the two identification strategies deliver similar results for the neutral shocks.

Panel A of table 2 shows that the investment-specific shocks account for 48 percent of the business cycle variation in hours and the implied path of hours is strongly correlated with actual hours. Consistent with previous work, neutral shocks account for only 6 percent of the variation in hours in the two-shock model and 4 percent in the one-shock model. In both of these cases the correlation of the implied hours paths with actual hours is quite weak. Overall, technology shocks account for 52 percent of the business cycle variation in hours. Moreover, according to the indicated confidence interval for this statistic, it is unlikely this percentage is below 30. The path of hours generated by the combined effects of the two technology shocks is highly correlated with actual hours. In sum, when compared with the results in table 1, including additional variables in the analysis has little impact on the findings for hours. A similar conclusion holds for the effect of technology shocks on output, as shown in panel B of table 2. As before, technology shocks are important for explaining the business cycle dynamics of output, and investment-specific shocks are more important than neutral shocks.

5. Robustness

The previous section demonstrated that technology shocks account for a significant fraction of the business cycle variation in hours worked and that investment-specific technology shocks are the most important of the two technology shocks considered. In this section I consider the robustness of these findings to various perturbations of the analysis. In addition, I consider the possibility that the shocks I have identified are not technology shocks, but reflect changes to other variables. From this analysis I conclude that the main findings are robust and that the shocks I have identified are unrelated to leading candidates for variables that may affect productivity and the real investment price in the long run.

5.1. Alternative Ways of Including Per Capita Hours in the Analysis

As I described in section 3.2, the appropriate way to include per capita hours worked into the analysis is a matter of some controversy. Here I consider two often suggested alternatives, first differencing and quadratic detrending, and focus on the larger two shock model. These alternative ways of including per capita hours imply somewhat smaller, but still large, effects of technology shocks on hours worked. Specifically, first differencing implies technology shocks account for 30% of business cycle variation in hours worked and that the largest contribution comes from I-shocks. Similarly, quadratic detrending per capita hours implies technology shocks account for 36% of business cycle variation in hours worked with I-shocks again the main contributor.[20]

While taken at face value these results do not seem to overturn the main findings, it is unclear how they should be interpreted. This is because the response of productivity to a positive I-shock is not consistent with theory under these alternative ways of including per capita hours since in both cases productivity converges to a negative value. There are other reasons to prefer the level specification. Certainly, the arguments of Christiano, *et. al.* (2002) point toward the level specification. In addition, the quadratic trend assumption seems questionable. First, when the hours series excludes farm hours, as it does here, the dip down in per capita hours in the middle of the sample is much less pronounced. This suggests that much of the downward trend in the early sample in the data which includes farm hours, as used by Francis and Ramey (2001), is due to the secular decline in farm hours. Excluding farm hours instead of quadratically detrending is a reasonable way of dealing with this trend. Second, while non-farm per capita hours do dip somewhat in the middle part of the sample, this period of relatively low hours worked coincides with higher inflation and nominal interest rates in the middle of the sample. It is not obvious that quadratically detrending hours is the best way to accommodate this co-movement. Indeed, it is possible that proceeding in that way may lead to specification error.

5.2. Assuming a Structural Break

Galí, López-Salido and Vallés (2001) have argued that the response of hours to neutral technology shocks before Paul Volker's chairmanship at the Federal Reserve was different from during and after that time. Using linearly detrended total hours worked, they estimate

[20] The impact of these changes on the responses of hours to the technology shocks is similar. For I-shocks hours continue to respond positively over the first 32 periods. The response of hours to an N-shock, however, is negative over this horizon. That the response of hours is negative following an N-shock when per-capita hours are first-differenced is consistent with the findings of Christiano, et. al (2002) and Francis and Ramey (2002).

hours to fall in the short run after a neutral technology shock in the pre-Volker period, before 1979:II, but to rise in the Volker-Greenspan period, after 1982:III. These findings are interpreted as arising due to an increased emphasis on price stability by the Federal Open Market Committee in the Volker-Greenspan period. Given the plausibility of the structural break hypothesis, it seems reasonable to ask whether the main findings reported here are somehow distorted by assuming structural stability throughout the sample period.

Unfortunately, the limited size of the two sub-samples suggested by Galí, *et. al.* (2002) presents some problems with assessing the impact of a structural break. Since the Galí, *et. al.* (2002) hypothesis is fundamentally about the conduct of monetary policy, it seems sensible to assess its effects by considering the larger two-shock model which includes the nominal interest rate and inflation. However, the two sub-samples are just too short to estimate this seven variable model with any reliability (Galí, *et. al.* (2002) estimated a model with only four variables, productivity, hours, inflation and a nominal interest rate.) I address this problem by studying a smaller five variable version of the larger two-shock model which excludes the two nominal expenditure share variables and is essentially the system estimated in Galí, *et. al.* (2002) appended to include the equipment price. The second problem is that the method used to extract the business cycle component of per capita hours becomes unreliable with short samples. I address this problem by considering forecast error decompositions associated with the estimated models. By comparing these with those derived from the larger model estimated over the full sample I can evaluate whether assuming a structural break matters for the main findings.

In figure 13 I display estimates of the short-run responses of the real price, labor productivity and hours for the two sub-samples. While not shown in the figure, the long run responses of the real price and productivity for the two shocks over the two sub-samples are consistent with theory. Differences in the short-run dynamics of these variables across the two sub-samples as shown in the figure does suggest the possibility of a structural break. Differences are also apparent across sub-samples for the response of hours. In contrast to the findings of Galí, *et. al.* (2002) there is little to choose statistically between the response of hours to N-shocks across the two sub-samples. However, the differences in the shape of the responses of hours to an I-shock are broadly consistent with the hypothesis of Galí, *et. al.* (2002). In particular, hours fall in the immediate aftermath of an I-shock before eventually rising, in the early period. In the later period the response of hours is uniformly positive.

Differences in the hours responses does not rule out the possibility that technology shocks account for a large fraction of the variation in hours in both sub-samples. This issue is addressed in table 3 where I display forecast error decompositions for various forecast horizons (in quarters) for the larger model estimated over the full sample (Panel A), and the smaller two-shock model over the sub-samples 1955:I-1979:II (Panel B) and 1982:III-2000:IV (Panel C). The results for the full sample confirm the findings reported in Table 2 for hours: technology shocks account for a significant fraction of the forecast error in hours over all the horizons and the contribution of I-shocks is large compared to the N-shocks. The findings for the two sub-samples are quite similar to the full sample results. The combined effects of the technology shocks is somewhat smaller in the sub-samples, especially at the shorter horizons, but the effects are still large. In addition the I-shocks continue to be the most important of the two shocks. I conclude that if one takes seriously the structural-break hypothesis then it leads to the same basic conclusions. Still, the evidence in favor of a structural break is not conclusive (e.g. Christiano, *et. al.* 2002 and Rudebusch 2002) and so the full sample results based on the larger seven variable system may be preferred if the five variable model has omitted variables and in fact there is sample period stability.

5.3. Trend Stationary Equipment Prices

In the model described in section 2.1 the standard one-shock identification scheme is valid if investment-specific technological change is deterministic. An obvious first test of whether the deterministic growth assumption is plausible is to test for trend stationarity. In the preliminary data analysis in section 3.2, standard statistical tests of the null of a unit root in the equipment price against the alternative of trend stationarity do not reject a unit root. Moreover, the Kwiatkowski, *et. al.* (1992) test of the null of trend stationarity versus the alternative of a unit root is strongly rejected. Questions of the veracity of the available statistical tests aside, this evidence is supportive of the approach taken in this paper. Nevertheless, the statistical tests are not perfect and it is worthwhile to examine the implications of assuming a deterministic trend in the level of investment specific technology.

I do this by adding the linearly detrended equipment price to the minimal and larger versions of the one-shock model, maintaining the one-shock assumption that only innovations to neutral technology have a long run effect on productivity. With these modified models the identified effects of technology shocks become a mixture of the responses to I-shocks and N-shocks identified with the two-shock models (not shown). One indication of this is that the contribution of technology shocks to the business cycle under the one-shock assumption resembles that found with the two-shock models (see the right-most columns of tables 1 and 2).

This result has two possible interpretations. First, it may be the case that investment-specific technological change is deterministic and that these modified one-shock models are accurately capturing the effects of neutral shocks. The difficulty with this interpretation is that the real equipment price is strongly negatively related to movements in investment and output in response to the estimated technology shock. That is, the real investment price *falls* in a boom driven by the supposed neutral shocks. One way this could happen would be if there are increasing returns to producing investment goods (see, for example, Murphy, Shleifer and Vishny (1989)). While this may be true, the degree of increasing returns required to reproduce the large price responses (they are similar to the price response to I-shocks over the first 32 quarters in figures 4 and 8) would seem to be implausibly large. The second, and in my view, more plausible interpretation, is that the estimated responses under the trend stationary assumption confound the effects of the two shocks and are not an accurate reflection of the true effects of neutral technology shocks.

5.4. Other Variables in the Estimated Systems

Now consider the effects of including additional variables in the estimated econometric models. There are any number of variables that might be considered. Here I consider the growth rate of M2, the growth rate of a measure of commodity prices (this is the Conference Board's index of sensitive materials prices deflated by my consumption deflator), and manufacturing capacity utilization. When these variables are added individually to the larger two-shock model and the responses and historical decompositions recalculated, the findings are not substantively altered. In all cases the contribution of technology shocks to hours variability exceeds 40 percent and investment-specific shocks remain, by far, the most important of the two technology shocks.

5.5. Are the Shocks "Technology"?

A common criticism of the identification strategy I have used in this paper is that changes in variables other than neutral and investment specific technology have had long run effects on productivity and the real investment price. If this is true, then one would need to broaden the interpretation of the shocks beyond that which I have given in this paper. However, one would still conclude that permanent shocks to the efficiency of producing consumption and investment goods are important for the business cycle.

Still, the interpretation of the shocks may influence one's view of the business cycle. As such it is interesting to assess whether these shocks are related to other non-technology variables that might influence the efficiency of producing consumption and investment goods. Leading candidates include capital tax rates, capital depreciation rates, and labor union membership.[21] Measures of these variables have secular trends and, to the extent that these

[21] It is straightforward to show that permanent changes in capital income taxes and the rate of capital depreciation affect aggregate labor productivity in the model presented section 2. In a two-sector version of this model with different factor share across consumption and investment good sectors, then changes in capital taxes and the rate of capital depreciation also affect the real price of investment goods. It is less clear how changes in unionization rates should affect labor productivity and the real investment price. Still, some authors, including Schmitz (2001), have argued that unions often bargain for work rules which have the result of lowering labor productivity. To the extent that unionization rates have fallen over my sample period and fallen by more in durable goods producing industries, it is reasonable to imagine that these have

trends reflect stochastic permanent components, then the shocks I have identified could be confounded with these other variables.[22]

Table 4 presents evidence which suggests that the shocks that I identify do not reflect shocks to these other variables. This table reports correlations of the identified shocks from the seven variable model with the growth rates of capital taxes, depreciation rates and union membership as a fraction of the labor force. Since the variables are only available on an annual basis the correlations are estimated using annual averages for the identified technology shocks. As Table 4 indicates, in all cases the correlations are small and not significantly different from zero. So, while in theory it is possible that the shocks I have identified may confound other shocks, in practice this does not seem to be a problem.

6. Conclusion

In this paper I have shown that when a standard procedure for identifying the effects of technology shocks is modified to take into account investment-specific technological change, then previous findings which suggest technology shocks are unimportant for business cycles are overturned. Results based on the sample period 1955-2000 suggest investment-specific technology shocks account for about 50 percent of the variation in hours worked and about 40 percent of the variation in output. At the same time, neutral technology shocks, the focus of the real business cycle literature, account for less than 10 percent of either output or hours variation.

Since these results are based on a procedure which abstracts from orthogonal transitory technology shocks, the findings may be viewed as representing a lower bound on the overall contribution of technology shocks to business cycles. Therefore, the results strongly suggest that technology shocks, or more generally, shocks to the efficiency of producing goods, are

influenced labor productivity and the real equipment price.

[22] My sources are as follows. For the capital tax I use an updated version of the series used by McGrattan (1994). For the depreciation rate I use the Bureau of Economic Analysis series on the rate of depreciation of the net stock of fixed assets and consumer durables. For union membership I use the series available from the Bureau of Economic Analysis. These data are only available annually.

important for understanding business cycles. Some investigation of the robustness of the findings was presented here, but of course more needs to be done. Still it does seem that business cycle research could benefit from being directed toward studying investment-specific technological change or other factors which influence the efficiency of producing investment goods but not consumption goods. The vanguard of research cited in this paper is a good foundation, but more work needs to be done here as well.

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Table 1. The Effects of Technology Shocks in the Minimal Models

Statistic	Two-Shocks: All Technology	Two-Shocks: Investment	Two-Shocks: Neutral	One-Shock: w/o Price Neutral	One-Shock: w Price Neutral
	Panel A: Hours Worked				
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.64	0.54	0.03	0.04	0.58
	$(0.35, 1)$	$(0.20, 1)$	$(0, 0.04)$	$(0, 0.08)$	$(0.33, 1)$
$\rho(H^m, H^d)$	0.80	0.79	0.34	0.32	0.80
	$(0.35, 0.96)$	$(0.45, 0.97)$	$(0.04, 0.65)$	$(-0.33, 0.59)$	$(0.61, 0.97)$
	Panel B: Output				
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.76	0.44	0.22	0.28	0.61
	$(0.52, 1)$	$(0.12, 0.86)$	$(0, 0.40)$	$(0, 0.55)$	$(0.38, 1)$
$\rho(Y^m, Y^d)$	0.86	0.73	0.55	0.60	0.83
	$(0.34, 0.97)$	$(0.50, 0.95)$	$(0.04, 0.80)$	$(-0.40, 0.86)$	$(0.72, 0.98)$

Table 2. The Effects of Technology Shocks in the Larger Models

Statistic	Two-Shocks: All Technology	Two-Shocks: Investment	Two-Shocks: Neutral	One-Shock: w/o Price Neutral	One-Shock: w Price Neutral
	Panel A: Hours				
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.52	0.48	0.06	0.04	0.38
	$(0.31, 0.95)$	$(0.35, 0.93)$	$(0, 0.11)$	$(0, 0.05)$	$(0.28, 0.75)$
$\rho(H^m, H^d)$	0.82	0.74	0.31	0.11	0.61
	$(0.82, 0.97)$	$(0.68, 0.95)$	$(-0.10, 0.60)$	$(-0.59, 0.19)$	$(0.46, 0.88)$
	Panel B: Output				
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.40	0.34	0.09	0.09	0.33
	$(0.16, 0.69)$	$(0.17, 0.64)$	$(0, 0.15)$	$(0, 0.15)$	$(0.22, 0.63)$
$\rho(Y^m, Y^d)$	0.71	0.65	0.24	0.16	0.57
	$(0.60, 0.90)$	$(0.55, 0.90)$	$(-0.23, 0.41)$	$(-0.42, 0.28)$	$(0.42, 0.85)$

Table 3: Forecast Error Decompositions for Hours

Horizon	All Technology	Investment	Neutral
Panel A: 1955:I-2000:IV			
1	46.3	44.6	1.7
4	59.3	58.6	0.7
8	57.8	57.3	0.5
12	54.4	51.6	2.8
32	61.3	43.3	18.8
Panel B: 1955:1-1979:II			
1	21.2	20.7	1.2
4	31.4	28.7	2.7
8	27.9	25.1	2.8
12	37.0	33.3	3.7
32	58.8	54.1	4.7
Panel C: 1982:III-2000:IV			
1	19.1	14.1	5.1
4	20.5	18.8	1.7
8	42.6	40.2	2.4
12	57.9	56.0	1.9
32	58.6	57.3	1.3

Table 4: Correlations of Alternative Shocks with Measured Technology Shocks

	Capital Tax	Unionization Rate	Depreciation Rate
	Neutral Technology Shocks		
Correlation	0.06	0.003	-0.02
Standard Error	0.14	0.14	0.18
P-value	0.66	0.98	0.91
	Investment-Specific Technology Shocks		
Correlation	-0.20	-0.07	0.03
Standard Error	0.18	0.14	0.12
P-value	0.27	0.61	0.82

Note: The sample period for the capital tax correlations is 1955-1997 and for the other correlations is 1955-2000.

Figure 1: Nominal and Real Prices of Investment

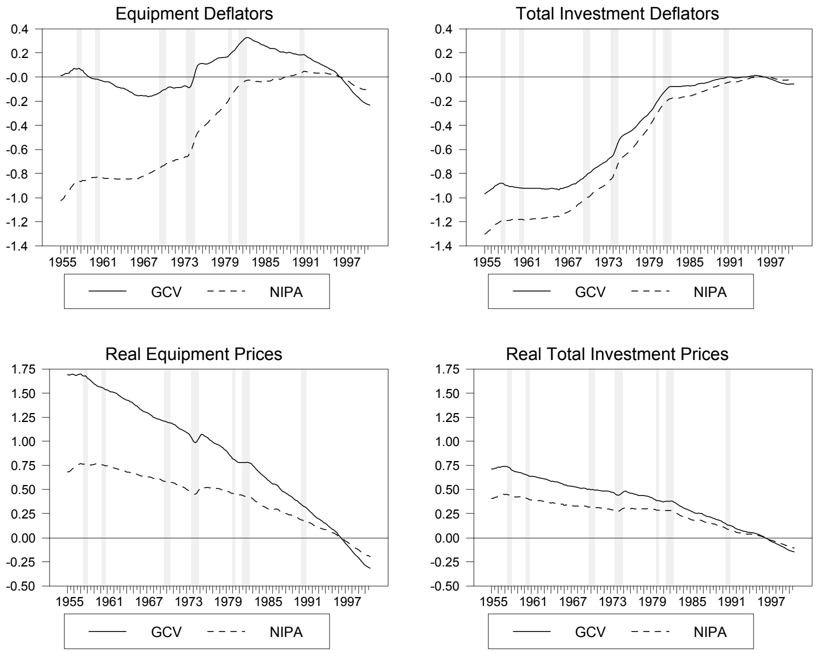


Figure 2: Investment Quantities and Prices

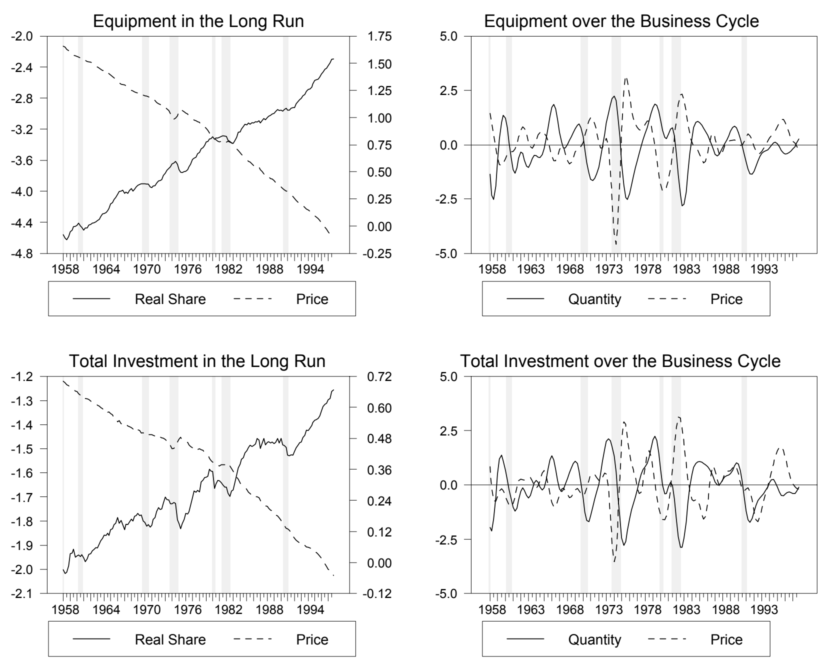


Figure 3: Variables in the Econometric Models

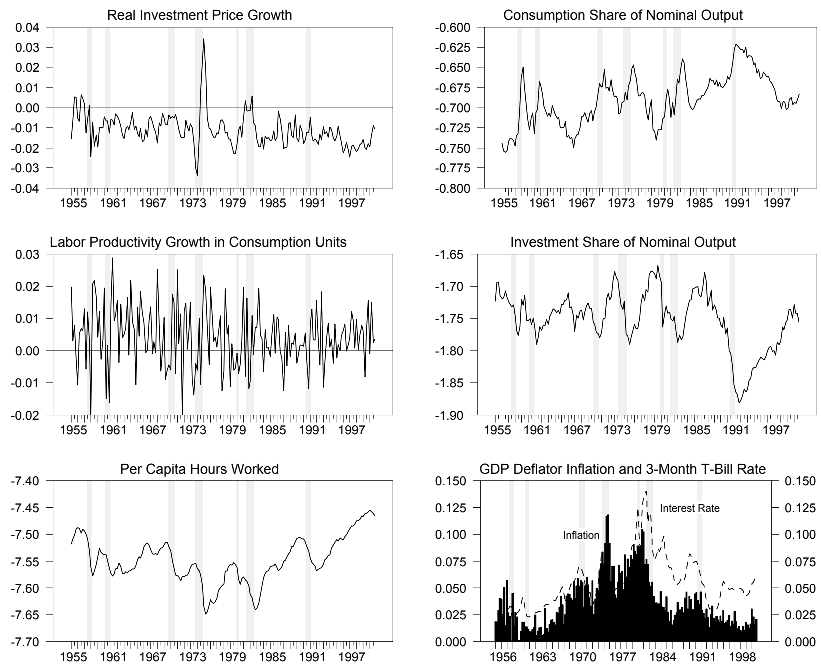


Figure 4: Long Run Responses in the Minimal Systems

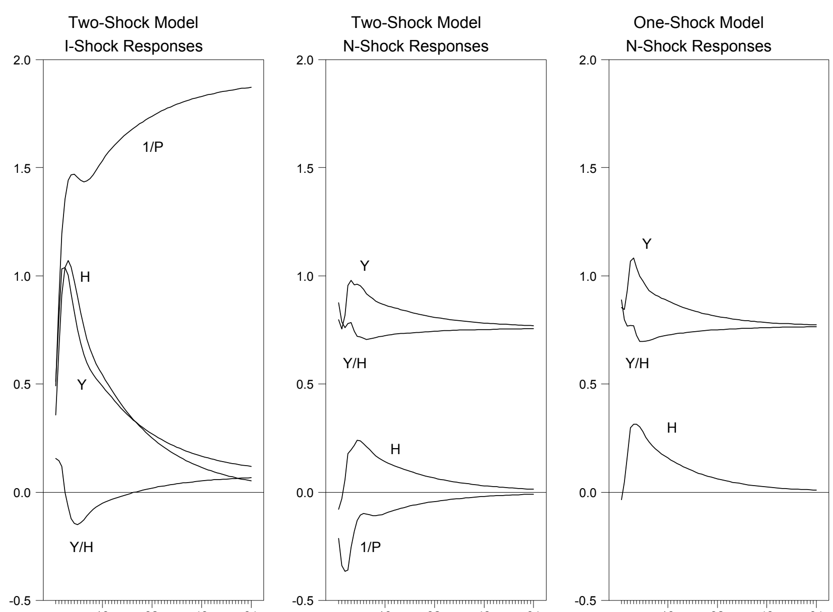


Figure 5: Short Run Responses in the Minimal Systems

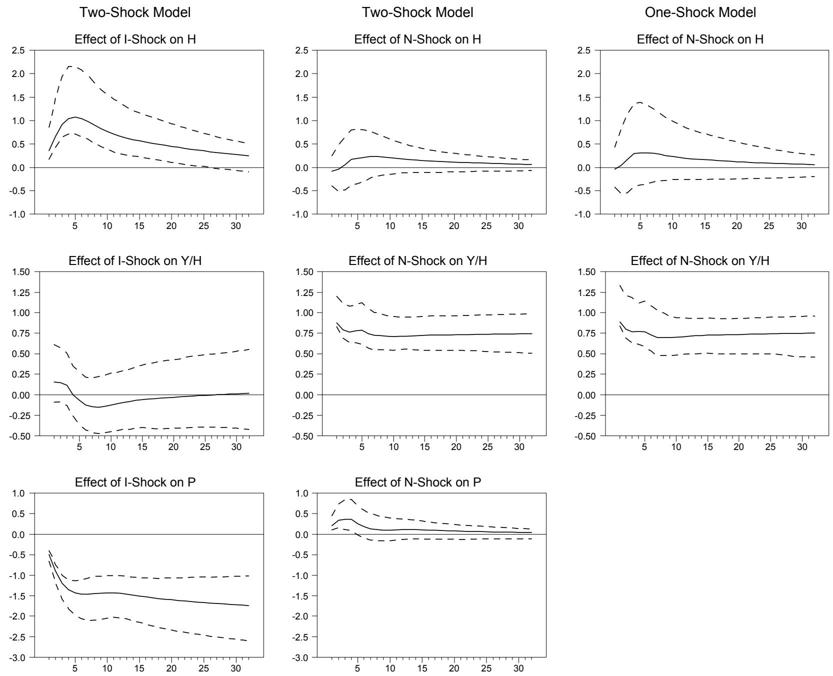


Figure 6: Actual and Technology-Driven Hours in the Minimal Two-Shock Model

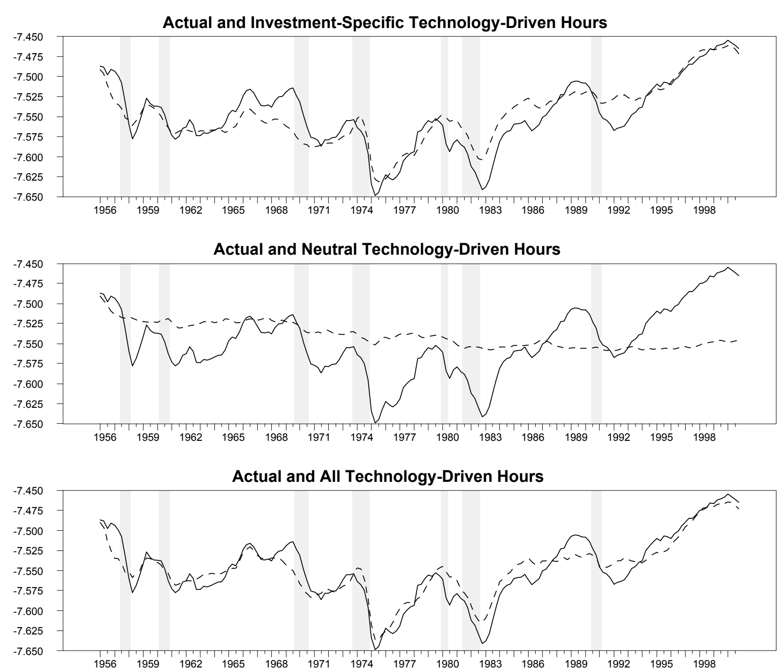


Figure 7: Effect of Technology on Hours in the Minimal Systems

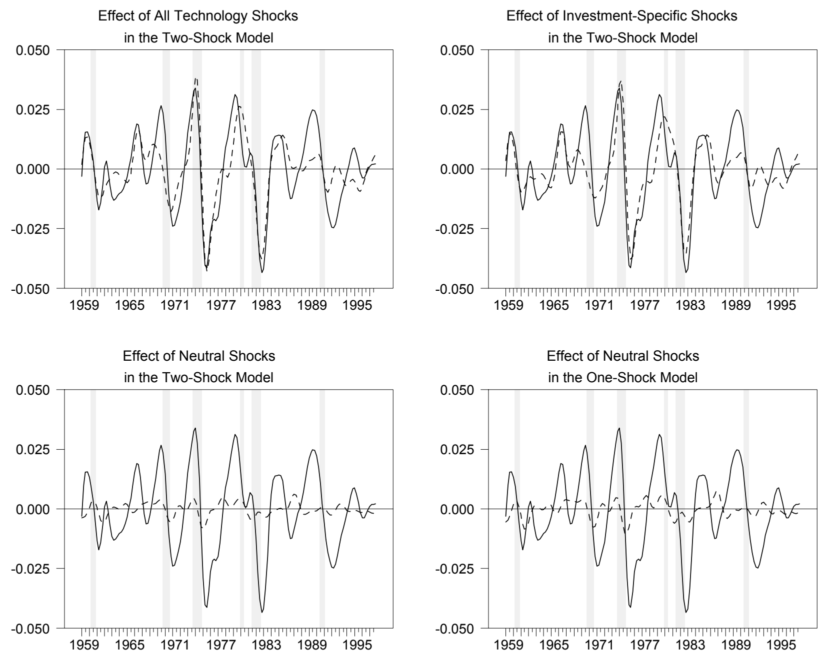


Figure 8: Long Run Responses in the Larger Systems

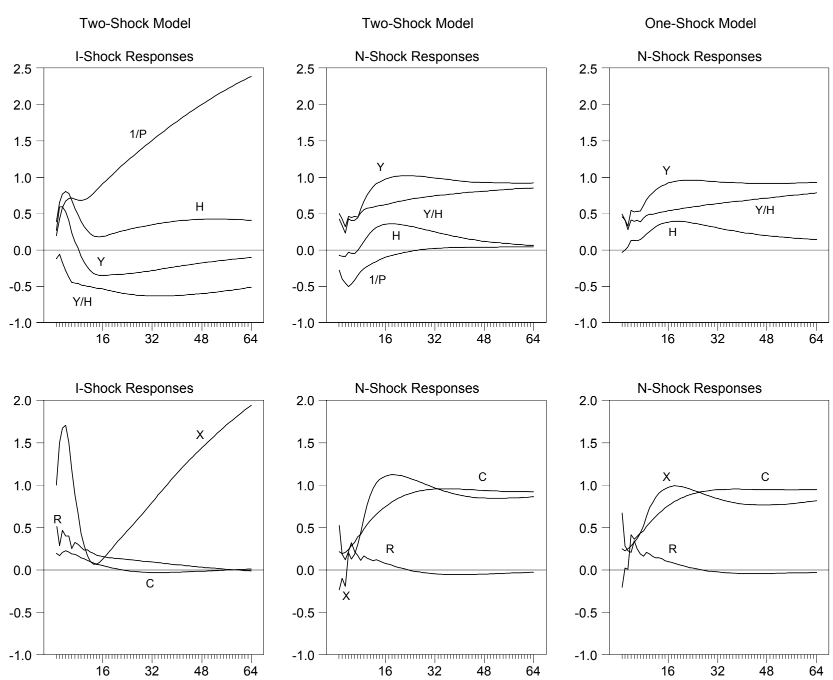


Figure 9: Short Run Responses in the Larger Systems

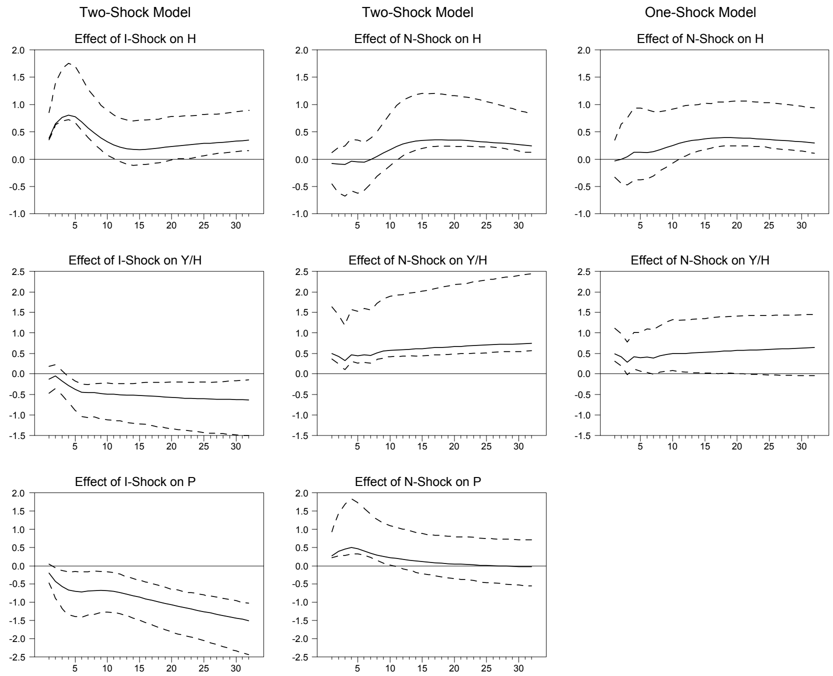


Figure 10: Short Run Responses in the Larger Systems

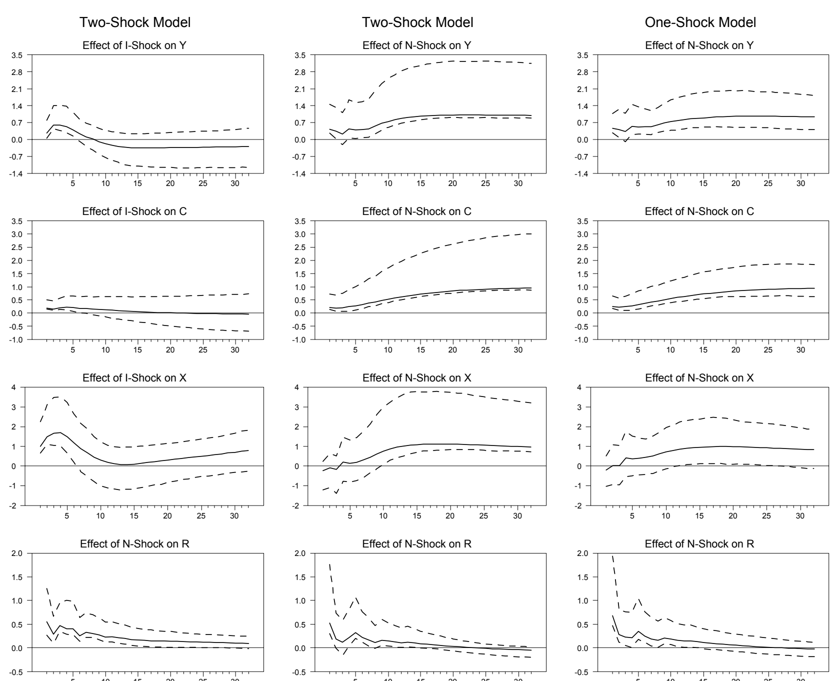


Figure 11: Actual and Technology-Driven Hours in the Larger Two-Shock Model

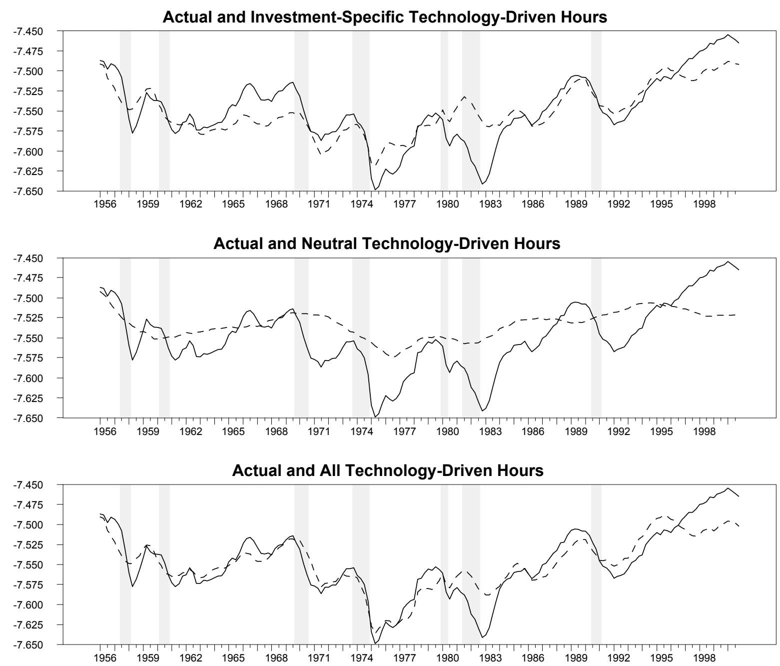


Figure 12: Effect of Technology on Hours in the Larger Systems

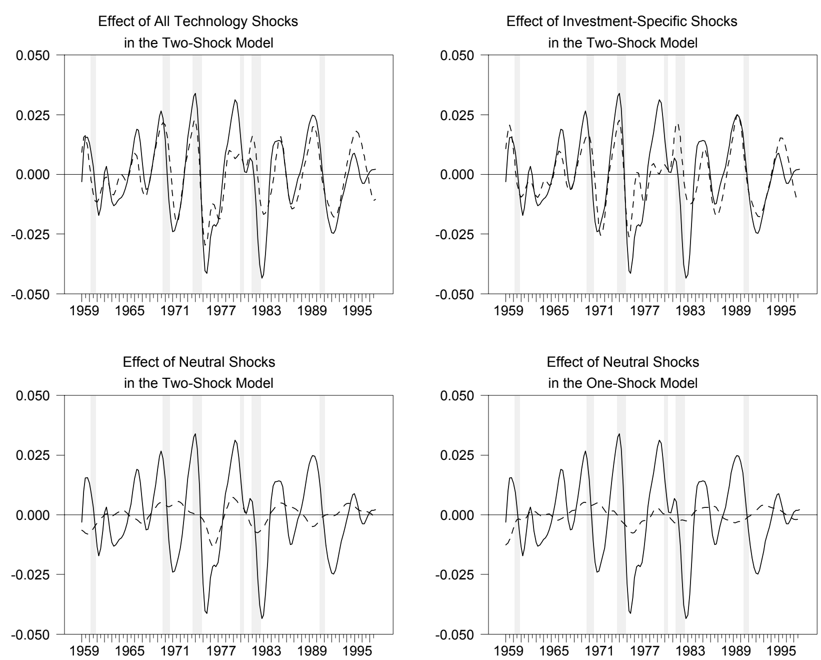
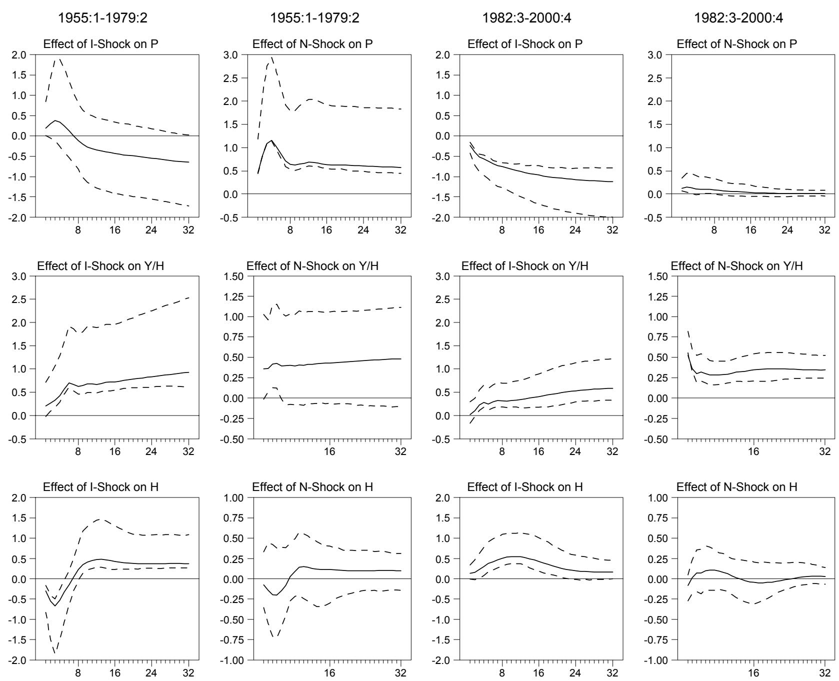


Figure 13: Responses to Technology Shocks 1955:1-1979:2 and 1982:2-2000:4



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