The Dynamic Effects of Neutral and Investment-Specific Technology Shocks

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Abstract

The neoclassical growth model is used to identify the short run effects of two technology shocks. Neutral shocks affect the production of all goods homogeneously, and investment-specific shocks affect only investment goods. The paper finds that previous estimates, based on considering only neutral technical change, substantially understate the effects of technology shocks. When investment-specific technical change is taken into account, the two technology shocks combined account for 40-60% of the fluctuations in output and hours at business cycle frequencies. The two shocks also account for more than 50% of the forecast error of output and hours over an eight year horizon. The investment-specific shocks account for the majority of these short run effects.

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1. Introduction

This paper investigates the short run effects on output and hours of neutral and investment-specific technical change. Permanent neutral technology shocks can be identified, if they are the only source of long run changes in labor productivity. Using this assumption, Galí (1999) and a growing literature find that technology shocks have only small short run effects.[1] Because this finding is very robust, it would seem to pose 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 potential source of technology shocks. Greenwood, Hercowitz and Krusell's (1997) finding that investment-specific technical change is the major source of economic growth, suggests it could be important for short run fluctuations as well. This paper argues that when both neutral and investment-specific technical change are taken into account, technology shocks matter a lot, and investment-specific shocks matter more than neutral shocks.

Introducing investment-specific technical change into a conventional real business cycle model motivates three long run identification assumptions. 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. Finally, the model predicts that investment-specific technical change raises labor productivity in the long run by a fixed fraction of its long run impact on the investment good price. I show how this prediction can be imposed as a new kind of long run restriction, and use it to refine my estimates.

[1] Figure 6, p. 268 is the clearest indication in Gali (1999) that technology shocks do not matter. Recent papers by Francis and Ramey (2003), Christiano, Eichenbaum and Vigfusson (2004), and Galí and Rabanal (2004) confirm the finding. This research builds on Blanchard and Quah (1989), King, Plosser, Stock and Watson (1991), and Shapiro and Watson (1988).

[2] While the real business cycle literature finds that transitory neutral shocks matter, these results are likely overstated. Real business cycle studies traditionally rely on Solow residuals to identify transitory shocks. It is widely accepted that Solow residuals are an error-ridden measure of neutral technology over short horizons. Under this view, the technology shocks driving most real business cycle models are implausibly large. See Basu, Fernald and Kimball (2004) for a recent discussion of Solow residuals.

When the methodology is applied to US data, neutral and investment-specific technology shocks combined account for 40-60% of the fluctuations in output and hours at business cycle frequencies. These shocks also account for more than 50% of the forecast errors in output and hours over an eight year horizon. The majority of these effects are accounted for by investment-specific shocks. The findings are robust to many perturbations of the analysis, and the identified shocks are unrelated to other variables, including those which might have long run effects on labor productivity and the real investment price.

The next section uses a simple real business cycle model to derive the identification assumptions at the heart of the analysis. Section 3 shows how these assumptions can be used to identify the effects of technology shocks. After this, the data are discussed, the main findings are presented, and the robustness of these findings is evaluated. The last section summarizes the findings and suggests directions for future research.

2. Theory

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

2.1. The 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

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

Here $\mathcal{E}_0$ is the expectations operator conditional on time $t = 0$ information, $U(\cdot,\cdot)$ is 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]

The model simplifies the one in Greenwood, *et. al.* (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 (2002) 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 which influence production possibilities, such as taxes, regulations and market

[3] An equivalent way to state this model replaces the inequality in (2) with $C_t/Z_t + \tilde{X}_t/\tilde{V}_t \leq K_t^{\alpha} H_t^{1-\alpha}$, 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). 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 specifications each have an equivalent representation as a two-sector model, with identical factor shares in the consumption good and investment good sector, and sector-specific technology terms given by A_t and $A_t V_t$, 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 main 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 non-diagonal.

structure. Disturbances to these variables might be transitory. Since the effects of transitory productivity shocks are not considered, the analysis delivers a lower bound on the magnitude of the short run effects of technology shocks broadly conceived.

2.2. 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 real 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:

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

where $Y_t = C_t + X_t$ and $Z_t = A_t^{1/(1-\alpha)}V_t^{\alpha/(1-\alpha)}$. 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 is stationary. From (5) 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

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

This implication is clearly different from the assumption 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,

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

The model can be extended to include additional exogenous shocks. As long as these shocks are transitory effects, the model will continue to satisfy (5) and $P_t = 1/V_t$. This leads to another useful implication of the model:

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

for all other shocks 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 (6) and (7), 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 $\alpha/(1-\alpha)$,

$$\lim_{j\to\infty} \frac{\partial \ln P_{t+j}}{\partial \varepsilon_{\upsilon t}} + \frac{1-\alpha}{\alpha} \lim_{j\to\infty} \frac{\partial \ln Y_{t+j}/H_{t+j}}{\partial \varepsilon_{\upsilon t}} = 0 \tag{9}$$

The specific constant of proportionality in (9) depends on the model having one sector and one capital good. However, versions of (9) with different constants of proportionality continue to hold for models with multiple capital goods and multiple sectors.[4]

Implications (6)-(9) are quite general, since they follow from the assumptions on preferences and technology necessary for balanced growth.[5] So, models with additional endogenous variables and propagation mechanisms, including models with nominal rigidities, are consis-

[4]For example, in the two capital good model with equipment-specific and neutral technical change studied by Greenwood, Hercowitz and Krusell (1997), the constant of proportionality associated with a permanent equipment-specific shock is $(1-\alpha_e-\alpha_s)/\alpha_e$, where α_e and α_s are the factor shares for equipment and structures.

[5]For balanced growth to be feasible, it must be possible to express technical change as labor-augmenting. With investment-specific technical change, then, balanced growth requires that the production function be Cobb-Douglas.

tent with (6)-(9). 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, *e.g.* 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, 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 (6)-(9).

2.3. Short Run Effects of Technology Shocks

It is useful to discuss 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 do 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 one 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 ($V_t X_t$), and 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 selections and the functional form for the utility function are consistent with much of the real business cycle 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, with the strongest response coming from the investment-specific shock (I-shock). The response of hours to a neutral technology shock (N-shock) is well understood. It 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 and so also is the response of hours worked.[6] This amplification is due to the shock affecting 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 response to an N-shock. 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 illustrate why estimates of the effects of technology shocks assuming that only neutral technology shocks affect productivity in the long run might be misleading. According to the aggregation theorem in Blanchard and Quah (1989, p. 670), the effects of technology shocks derived from vector autoregressions in productivity and hours are robust to the presence of additional technology shocks which 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 technology shock is the sum of the hours responses to one-standard deviation shocks 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. These considerations suggest the short run

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

effects of technology shocks found in the previous literature might not be robust to the presence of investment-specific technical change.[7]

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 pro-cyclicality of hours, consumption and investment.[8] 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 real business cycle literature studies investment-specific technical change and finds that it might have large short run effects. The earliest paper is Greenwood, Hercowitz and Huffman (1988). Other papers include Campbell (1998), Christiano and Fisher (1998), Fisher (1997), and Greenwood, Hercowitz and Krusell (2000). The effects of technology shocks derived from these studies depend on the specifics of the propagation mechanism imbedded in the model under consideration. The advantage of the econometric approach described in the next section is that it takes a weaker stand on the nature of the propagation mechanism.

3. Econometric Strategy

The econometric strategy is based on three assumptions which summarize the long run implications of models for which (6)-(9) hold. These are summarized as follows.

Assumption 1. Only investment-specific technology shocks affect the real investment price in the long run.

[7]For the calibrated model underlying figure 1, it is straightforward to derive the probability limit of the response of hours one would obtain from a vector autoregression in productivity and hours under the (false) assumption that neutral shocks are the only shock 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 the previous literature understates the contribution of technology shocks to short run fluctuations.

[8]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 neutral or investment-specific technology shocks affect labor productivity in the long run.

Assumption 3. Exogenous investment-specific technology shocks which lower (raise) the real 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.[9]

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

$$y_t = \Phi(L)\varepsilon_t \tag{10}$$

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 (this could be the first difference of log per capita hours, or some other stationary transformation of hours), q_t is a vector of other endogenous variables in the model, and $\Delta \equiv 1 - L$.

Assume that $\Phi(L)$ is invertible and that its inverse is well-approximated by a finite order lag polynomial.[10] The (approximate) vector-autoregressive representation of (10) can be written,

$$Ay_t = \Gamma(L)y_{t-1} + \varepsilon_t, \tag{11}$$

where $\Gamma(L)$ is an N'th order matrix lag polynomial and A is a matrix conformable with y_t,

[9] The estimation strategy borrows from Shapiro and Watson (1988). See Basu and Fernald (1998) for a different strategy for identifying neutral technology shocks which does not rely on long run restrictions. Basu, Fernald, Fisher and Kimball (2005) show how to extend this methodology to identify sector-specific technology shocks.

[10] 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 infinte order vector-autoregressive representation of the two variable system with Δp_t and Δa_t is almost identical to the representation with just one lag.

normalized to have ones along the diagonal. With estimates of A and $\Gamma(L)$, (11) is simulated to derive the impulse response functions of interest. Equation (11) is estimated using a series of instrumental variables (IV) regressions.

The first equation of (11) is

$$\Delta p_t = \Gamma_{pp}(L)\Delta p_{t-1} + \Gamma_{pa}(L)\Delta a_t + \Gamma_{ph}(L)h_t + \Gamma_{pq}(L)q_t + \varepsilon_{vt}, \tag{12}$$

where the $\Gamma_{xy}(L)$'s here and below are the relevant lag polynomials. According to (12), the contemporaneous effects of all non-ε_{vt} shocks influence Δp_t through Δa_t, h_t and 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 polynomials associated with Δa_t, h_t and q_t. That is each $\Gamma_{pj}(L)$, $j = a, h, q$ can be written, $\Gamma_{pj}(L) = \tilde{\Gamma}_{pj}(L)(1 - L)$. It follows that (12) becomes

$$\Delta p_t = \Gamma_{pp}(L)\Delta p_{t-1} + \tilde{\Gamma}_{pa}(L)\Delta^2 a_t + \tilde{\Gamma}_{ph}(L)\Delta h_t + \tilde{\Gamma}_{pq}(L)\Delta q_t + \varepsilon_{vt}. \tag{13}$$

Innovations to the real investment price affect the contemporaneous values of Δa_t, h_t and q_t. Consequently (13) 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. So (13) is estimated by IV, using N lags of y_t as instruments. The coefficients of the first equation of (11) are found by unravelling the resulting regression coefficients. The residuals from (13) are the estimates of ε_{vt}, $\hat{\varepsilon}_{vt}$.

Now consider the second equation of (11). By a similar argument to before, assumption 2 implies the long run multipliers from h_t and q_t to Δa_t are zero. It follows that the second equation of (11) can be written,

$$\Delta a_t = \Gamma_{ap}(L)\Delta p_t + \Gamma_{aa}(L)\Delta a_{t-1} + \tilde{\Gamma}_{ah}(L)\Delta h_t + \tilde{\Gamma}_{pq}(L)\Delta q_t + \varepsilon_{at}, \tag{14}$$

where the $\tilde{\Gamma}_{aj}(L)$, $j = h, q$ are defined in the same way as the similar terms in (13). As before, this equation is estimated by IV and the resulting coefficient estimates are used to assign values to the second row of coefficients in (13). The instruments are $\hat{\varepsilon}_{vt}$ and N lags of y_t. The residuals from (14), $\hat{\varepsilon}_{at}$, are the estimates of ε_{at}. Including $\hat{\varepsilon}_{vt}$ as an instrument ensures $\hat{\varepsilon}_{at}$ 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) widely used method because the real price is included in (14) and the residuals from (12) are included in the instrument list.

The first two equations of (11) are exactly identified. It is straightforward to show that there exists a family of parameterizations of the remaining rows of (11) 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 (11) sequentially by IV, using the residuals from the previously estimated equations and N lags of y_t as instruments. Following this procedure does not impose any restrictions on the impulse responses of interest.

So far, assumption 3 has not been used. Indeed, it is possible to identify variables' responses to the two technology shocks using only assumptions 1 and 2. There are two reasons to use assumption 3. First, it is a way to test the model. Using auxiliary information about the share of capital in production, assumption 3 and the viability of the identification strategy can be tested. Second, imposing an overidentifying restriction should improve the precision of the estimates.

The Appendix shows that, under assumptions 1 and 2, assumption 3 implies a simple linear restriction on the coefficients of the second equation of (11). To state this restriction, define $C(L) = A - \Gamma(L)L$ and let the ij'th element of $C(1)$ be denoted c_{ij}. In the context of the model described in section (2.1), the restriction is

$$\frac{1-\alpha}{\alpha}c_{21} - c_{22} = 0. \tag{15}$$

In practice, (15) is rarely rejected at conventional significance levels. With the baseline dataset discussed in the next section, the marginal significance levels range from 16% to

60%. Consequently, unless otherwise noted, the results involve estimates of (11) in which (15) has not been rejected and is imposed.

It is important to address the statistical properties of this methodology. Cooley and Dwyer (1998), Erceg, Guerrieri and Gust (2004), and most recently Christiano, Eichenbaum, and Vigfussen (2005) discuss situations in which long run restrictions might yield misleading results. Obviously, if assumptions 1-3 do not hold then the analysis might be invalid. Less obvious is how well the methodology works in small samples when the assumptions do hold. Christiano, *et. al.* (2005) document the small sample properties of a business cycle model with a neutral technology shock. They find that empirical standard errors accurately reflect the true uncertainty in their estimates, and that including variables such as the real interest rate or the investment-output ratio is useful for eliminating small sample bias. The previous literature only considers exactly identified empirical models. Thus, the overidentifying restriction proposed here, (15), should improve the methodology's performance.

4. Data

This section describes the data. The Appendix contains a more detailed description.

4.1. The Real Price of Investment

Clearly, the real investment price is a crucial input to the analysis. This price is measured as the ratio of an investment deflator and a consumption deflator. The consumption deflator corresponds to nondurable and service consumption, the service flow from consumer durables and government consumption, and is derived directly from the National Income and Product Accounts (NIPA). Greenwood, Hercowitz and Krusell (1997) emphasize the lack of quality adjustment in the NIPA investment deflators. Their estimate of the contribution to growth of investment-specific technical change is based on Gordon's (1989) deflator for producer durable equipment. Gordon argues that the NIPA equipment deflators at the time his book was written were seriously mismeasured because of their treatment of quality change. As described in Moulton (2001), the NIPAs currently incorporate hedonic methods to quality adjust computers, semiconductors, software and digital telephone switching equipment, but they do not quality adjust other types of capital equipment. Consequently, there is still quality bias in the NIPA equipment deflator, especially in the years prior to 1980 when the share of investment in quality adjusted equipment is relatively small. Residential structures investment is extensively quality adjusted, but non-residential structures investment is not.

Greenwood, *et. al.* (1997) show that the real price of producer durable equipment derived from Gordon's deflator has a pronounced downward secular trend. Using a model similar to the one in section 2.1, they find that the implied investment-specific technical change accounts for 58 percent of output growth between 1954 and 1990.[11] Greenwood, *et. al.* (1997) arrive at their estimates by extending Gordon's original sample, which ends in 1983, with a rough bias adjustment to the NIPA data. Cummins and Violante (2002) calculate a more systematic update of the Gordon data. For component deflators not already quality adjusted in the NIPAs, they estimate econometric models of the bias adjustment in Gordon's deflators. They combine the deflators estimated with these models with the quality-adjusted NIPA deflators to construct a deflator which extends to 2000 for all of producer durable equipment. Their findings confirm the Greenwood, *et. al.* (1997) result that investment-specific technical change is a major source of growth.

Four investment deflators are considered. The first measure is "equipment." It is just the GCV equipment deflator. The second is "total investment," a broader measure constructed with the GCV deflator and the NIPA deflators for non-residential and residential structures, consumer durables and government investment. This deflator corresponds to the measure of investment often used in real business cycle studies. The deflators must be quarterly series for the econometric analysis. Since the GCV series is an annual series, it must be interpolated. The appendix describes in detail how this is done. Briefly, the procedure maintains the year-

[11] Greenwood, *et. al.* (1997) consider and reject several mechanisms which in principle might account for the secular trend in the real investment price instead of investment-specific technological change. One important example 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) argue that this hypothesis requires implausible parameter values.

to-year trends in the more accurate GCV series, and uses the corresponding NIPA deflator to derive within year fluctuations. The two other deflators used in the analysis are the NIPA-only counterparts to the GCV-based deflators.

Figure 2 displays the two GCV-based and NIPA-based investment deflators and the associated real investment prices for the sample period 1955:I-2000:IV.[12] 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 points. First, the quality bias in the NIPA deflators is quite large, suggesting that they might not be reliable for constructing real prices. It does not seem that a single adjustment to the average growth rate accurately reflects the nature of the mismeasurement. Second, consistent with Cummins and Violante (2002) and Greenwood, *et. al.* (1997), equipment-specific technical change is substantial after 1955. There is a 200 percent drop in the real equipment price.[13] Third, the real total investment price declines by much less, but still has a secular trend. The weaker trend in this price might 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 embody less quality adjustment. For example, Gort, Greenwood, and Rupert (1999) estimate significant quality bias in the NIPA deflators for non-residential structures.

Figure 3 provides intuition for why the real investment price might be important for understanding macroeconomic dynamics (similar plots appear in Greenwood, *et. al.* (1997, 2000).) The top plot reproduces the GCV-based real equipment price from figure 2 along with the log ratio of the quantity of equipment in units of capital to GDP 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

[12] There are three reasons to exclude data before 1955. First, the real business cycle literature often focuses on the post-Korean war era (see for example, Prescott 1986). Second, the interpolations of the equipment deflator before 1955 are questionable because the quality bias in the NIPA data is much stronger than later in the sample. Third, estimates of neutral technology shocks are sensitive to including variables associated with monetary policy. This suggests the sample should begin after the Treasury Accord of 1951.

[13] The changes in the real equipment price in 1973-74 are partly an artifact of 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 investment-specific technology shocks.

technical change for capital accumulation and growth.[14]

The bottom plot in figure 3 displays the business cycle components of real equipment and GDP.[15] This shows a clear negative relationship between the GCV-based real equipment price and output, strongly suggesting a role in short run fluctuations for shocks to the cost of producing investment goods. The unconditional contemporaneous correlation is strongly significant with a point estimate of -0.54 and standard error of 0.09. This correlation is even stronger with the NIPA real equipment price, and is somewhat weaker, but still significantly negative, with total investment prices. Some of the latter difference is probably due to residential investment having a strong "demand"-driven component.

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

4.2. Baseline Dataset

This subsection describes the baseline set of variables used in the analysis. To measure the effects of technology shocks on hours and output, the econometric model in section 3 requires only variables measuring the growth rate of the real investment price, the growth rate of average labor productivity, and per capita hours worked. The GCV real equipment price is the baseline measure of the real investment price because it contains more quality adjustment than its NIPA counterpart or either total investment price. The main findings

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

[15] Business cycle components are derived using Christiano and Fitzgerald's (2002) implementation of the band-pass filter, excluding frequencies higher than one and a half years and lower than eight years.

are robust to using the GCV-based total investment price and the NIPA counterparts to the GCV prices. The Appendix presents these findings.

Labor productivity is measured by the non-farm business series published by the Bureau of Labor Statistics (BLS). This measure is used by Galí (1999). To retain consistency with the growth model, labor productivity is expressed in consumption units using the same consumption deflator as that underlying the baseline real investment price. The literature also considers another BLS productivity measure which includes the farm sector. The implications of using this series are discussed in section 6.

The way in which hours should be included in the analysis is not settled in the literature. The baseline results are based on including per capita hours in log levels. The baseline measure of per capita hours is the BLS hours worked series corresponding to the baseline productivity measure, divided by the civilian non-institutionalized population over the age of 16 years. The literature considers several other ways of including hours. The main alternatives and the impact using them has on the findings is discussed in section 6.

Considering other variables in the analysis is important for assessing the findings' robustness. Erceg, Guerrieri and Gust (2004) and Christiano, Eichenbaum and Vigfusson (2005) argue that the small sample properties of long run identifying schemes can be improved by including additional variables. Christiano, *et. al.* (2004) argue that the business cycle contribution of neutral technical change might be overstated by excluding certain variables. These papers motivate including inflation, a nominal interest rate, and the nominal expenditure shares of consumption and investment. Inflation is measured with the baseline consumption deflator and the nominal interest rate is the 3-month Treasury Bill rate. The expenditure shares are constructed using nominal non-farm business output, nominal consumption corresponding to the baseline consumption deflator, and nominal total investment as described in section 4.1.

5. Baseline Results

This section describes the findings based on the baseline dataset. The first sub-section focuses on the parsimonious system with the real price, productivity and hours. Given the connection of the methodology with the previous literature, these findings are compared with the same system without the real price, under the assumption that only neutral technology shocks have permanent effects on productivity. The second sub-section discusses the implications of adding variables to the two parsimonious systems. Up to this point, the estimates are based on the full sample from 1955:I to 2000:IV. The third sub-section discusses reasons to split the sample around 1980, and the implications of doing this. All the estimates are based on four lags in (11). Throughout, assumption 3 is imposed with a value of capital's share, α, equal to 1/4 in (15). This is a compromise between assuming the equipment price is a proxy for the price of total investment, or that it only applies to equipment in a production function which also includes structures. The results are not sensitive to reasonable perturbations of α. Regardless of the number of variables in the empirical model, or whether the sample is split, the results show an important role for technology shocks in short run fluctuations, and that investment-specific technology shocks are more important than neutral shocks.

5.1. Parsimonious Specifications

Figure 4 displays estimated dynamic responses of the real investment price, labor productivity, hours and output to the two technology shocks using the parsimonious specifications. As before "I-shock" stands for "investment-specific shock" and "N-Shock" stands for "neutral technology shock." The term "one-technology" is used to indicate estimates under the neutral-technology-only hypothesis and the term "two-technology" is used to indicate estimates under the hypothesis that investment-specific technical change is also present. The responses are to one-standard deviation positive innovations in period 1. In figure 4 the solid lines are responses to I-shocks, the short-dashed lines are responses to N-shocks using the two-technology model, and the dotted lines are responses to N-shocks using the one-technology model. The solid circles and open circles denote significance at the 5% and 10% levels, respectively.[16]

The responses to the I-shock are large and significant. The peak response of hours is 1.0% and the response is almost always significant at the 5% level. After an initial increase, the response of productivity declines below zero before rising to its long run positive value. It becomes significantly positive after 5 years. Output responds similarly to hours and is always significant. The price response is smaller in the short run than in the long run, but it is always significant at the 5% level. The qualitative nature of these responses is consistent with the theoretical responses in figure 1.

The response of hours to the N-shock in the two-technology model is about a third of its response to the I-shock, while the output response is a little stronger. The output response is always significant, but the hours response is never significant. The two-technology identification has the advantage of yielding the response of the investment price to an N-shock, and this rises significantly after an N-shock. This is consistent with a simple extension of the model in section 2.1 with curvature in the production possibilities frontier for consumption and investment, adding support to the interpretation of the N-shocks as being genuine neutral technology shocks.

The responses to an N-shock in the one-technology model are similar to the two-technology case. The productivity response is close to its comparable two-technology response, but the hours and output responses are always below. The hours response is only a quarter of the response to an I-shock and is never significant. The responses of hours and productivity in the two-technology case show that the assumptions of Blanchard and Quah's (1989) aggregation theorem do not hold empirically. Consequently, it should not be surprising that the response of hours in the one-technology model is *not* the average of the N-shock and I-shock responses in the two-technology model.[17]

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

[17]Including real investment price growth in the one-technology model has little effect on the estimated responses (not shown.)

The similarity of the two-technology responses with their theoretical counterparts supports the view that the estimated shocks are genuine. So it makes sense to consider the shocks' contribution to short run fluctuations. Consider the behavior of hours. The weak and insignificant response of hours to an N-shock suggests this shock is not important for short run fluctuations. On the other hand, the large and statistically significant response of hours to an I-shock suggests this shock *is* important. These conjectures are verified by examining the left-hand column of figure 5. This shows actual hours and the historical decompositions of hours derived from the two-technology model, assuming only one of the technology shocks is operational over the sample.[18] The first row shows that I-shocks account for a large part of the variation in hours worked, particularly around recessions. They account for much of the boom of the 1990s, which is consistent with a common interpretation of this time period. N-shocks are less related to the business cycle. (the decomposition under the one-technology identification, not shown, is similar).

The right-hand column of figure 5 presents the business cycle components of actual hours (solid lines) and hours corresponding to the historical decompositions. The variation in hours due to N-shocks in the second row is small. This is consistent with the previous finding in the literature that N-shocks are unimportant for the short run. In contrast, the I-shock (first row) generates a large amount of business cycle variation.

Tables 1 and 2 quantify the findings in figure 5 and provide additional information about output. Table 1 displays the forecast error decomposition of hours and output implied by the estimated two-technology model. The connection between forecast error decompositions and contributions to the business cycle is not direct. Table 2 displays the ratio of the variance of the business cycle components of the technology-shock-only driven data (such as is displayed in the right-hand column of figure 5) to the variance of actual hours and output. Point estimates are in bold and 95% confidence intervals are in parenthesis below.

[18] The predicted time path of hours for a given model and shock is based on simulating (11) 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 the left-hand plots.

According to Table 1, from one to eight years 54% to 74% of the forecast error of hours is accounted for by technology shocks. These contributions are statistically significant. I-shocks are much more important than N-shocks for hours. An even greater fraction of the forecast error of output is due to the technology shocks, never lower than 88%. These contributions are always statistically significant. For output, N-shocks account for about two thirds of the overall technology contribution.

Table 2 indicates that at business cycle frequencies, technology shocks are very important for both hours and output.[19] Technology shocks account for 68% of the variation of hours and 79% for output, and both of these contributions are statistically significant. I-shocks account for almost all the effects of technology on hours. In contrast to the forecast error decomposition, I-shocks are more important than N-shocks for output as well. The statistical significance of the variance ratios of hours and output strongly suggest a major role for technology shocks, in particular I-shocks, in driving the business cycle.

5.2. Adding Variables to the Analysis

Now consider adding the expenditure shares, inflation and the interest rate to the parsimonious systems. In the seven variable system, the main findings are similar to those for the three variable model. However, adding variables does complicate the analysis somewhat.

Fisher (2003) shows that when Assumption 3 is not imposed, the long run response of labor productivity to an I-shock is small, and only turns positive after about 20 years. It is not surprising that productivity initially declines, but it seems implausible that it takes so long for it to turn positive.[20] In results not reported here, adopting assumption 3 has little impact on the time for productivity's response to turn positive after an I-shock. This finding

[19] 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 1 (and table 2, below) reflect these slight correlations.

[20] Hornstein and Krusell (1996) argue that investment-specific technical change can lead to a long negative impact on productivity due in part to learning-by-doing factors. According to their analysis a twenty year negative response of productivity is implausible.

and the one in Fisher (2003) might suggest that the technology shocks are not accurately estimated in the seven variable system.

To address this possibility, the seven variable system is estimated with an additional restriction. Specifically, the estimation strategy involving assumptions 1-3 is appended to include:

Assumption 4. The response of productivity to an I-shock is positive after 8 years.

Imposing assumptions 3 and 4 means that the estimation involves two overidentifying restrictions on (11). These two restrictions are not rejected at conventional significance levels using the baseline dataset.[21] Figure 6 displays the resulting dynamic responses for the same variables as in figure 4, as well as consumption and investment. This figure also displays responses based on the comparable one-technology model without the investment price.

Including the additional variables has a noticeable impact on the I-shock responses. The magnitudes of the peak responses of hours and output are similar to before. However, now the hours response has two humps, and output and investment have an initial hump before rising to their long run values. The only variable which behaves like its theoretical counterpart in figure 1 is consumption, which rises slowly to its long run value. Productivity has been restricted to be zero at 32 quarters, but is never very significant before then. The price response is quite close to the same response in the three-variable system. With the exception of the productivity response, most of the I-shock responses are significant for about half of the 32 quarters.

The one- and two-technology N-shock responses of the investment price, labor productivity, hours and output are similar in magnitude and shape to the comparable responses in figure 4. The main differences are that these variables rise more slowly to their peaks

[21] Unlike assumption 3, which is a linear restriction on a single equation, assumption 4 is a cross-equation restriction, which means the equations of the model must be estimated simultaneously. This is accomplished using the generalized method of moments subject to assumption 3 and the restriction that the response of productivity to an I-shock is exactly zero at 32 quarters after a shock. In practice, the second condition is sufficient for assumption 4 to hold. The Hansen (1982) $J-$statistic can be used to test the two overidentifiying restrictions. Using the baseline dataset the $J-$statistic is 3.39. The probability that a Chi-squared random variable with two degrees of freedom exceeds this value is 18.4 percent.

and take longer to attain their long run values. So, as with the parsimonious systems, the two strategies for identifying N-shocks seem to be identifying roughly the same shock. Consumption rises gradually to its long run value and investment is hump-shaped. The responses of productivity under the one-technology identification and the investment price under two-technologies are only significant initially after an N-shock. Hours responds significantly under the one-technology identification, but like investment, it is not significant under the two-technology scheme. The remaining responses are mostly significant at the 5% level.

As before, the plausibility of the responses in figure 6 can be assessed by comparing them with the theoretical counterparts in figure 1. Since the responses to N-shocks of productivity, hours and output are similar to those with the three variable system, these responses are not at odds with theory. The consumption and investment responses to N-shocks are also broadly consistent with the theory. The responses of hours, output and investment to an I-shock are qualitatively different from those in figure 1, but they might be valid. Consider an economy subject to costly reallocation across sectors. The first humps may be due to an initial burst of activity as firms seek to exploit the new technology. Some of these firms fail, and a costly and time consuming reallocation of resources toward successful firms ensues. The second hump in hours and the gradual rise in output and investment might follow this reallocation as the successful firms finish implementing the new technology. This description seems consistent with the commercial development of the internet. Gort and Klepper (1982) report that many industries developed from the invention of new products go through initial stages of entry by large numbers of firms, followed by a "shake-out" which leads to large number of firms exiting the industry, then relatively stable market conditions. Jovanovic and MacDonald (1994) describe a model to address this empirical evidence.[22] For now, the results are taken to be valid.

Figure 7 and tables 2 and 3 show the contributions of the technology shocks to short

[22] Beaudry and Portier (2004) identify responses to innovations in the stock market which have the two-hump feature as well.

run fluctuations. They essentially confirm the main findings from the three variable system. Figure 7 is somewhat different from figure 5, with hours due to I-shocks tracking actual hours less closely, and hours due to neutral shocks mainly a-cyclical. The combined effect of the shocks seems large and I-shocks are clearly more important for short run fluctuations than N-shocks. A notable difference with the three variable system is that here there is more room for monetary policy to play a role during the 1979-1982 period. In addition, I-shocks now track the business cycle component of hours quite closely in the 1990s.

The quantitative results in Table 3 show that the two technology shocks combined account for a large and statistically significant part of the forecast error in both hours and output. I-shocks are more important for hours and N-shocks are more important for output. Table 2 shows that the combined contribution to business cycle fluctuations of the technology shocks is lower than with the three variable system, but is still large and statistically significant for I-shocks. I-shocks are more important over business cycle frequencies than N-shocks, for both output and hours.

5.3. Should the Sample be Split?

There are several reasons to consider splitting the sample. First, the character of the impulse response functions based on the full sample displayed in figure 6 might be suspect. In particular, they might indicate a misspecification due to a structural break in the data which renders estimation over the full-sample invalid. Second, the average rate of investment-specific technical change might have changed over the sample. Third, some observers view the conduct of monetary policy to have changed substantially after 1980. Finally, there has been a substantial decline in the volatility of many macroeconomic variables which may be due to a structural shift.

Cummins and Violante (2002), Greenwood and Yorukoglu (1997), and Hornstein and Krusell (1996) argue that the average rate of decline of the real equipment price changes after 1970. Figure 2, where the four measures of the investment price are plotted, suggests such a break may have occurred in the early 1980s, when the personal computer began to be widely used in business. Formal tests of a structural break in the growth rate of the baseline real investment price, using the Bai and Perron (1998, 2003) methodology, suggest exactly one of them occurred, in 1982.[23] Before 1982 the mean rate of decline in the baseline equipment deflator is 0.84%, and after 1982 it is 1.49%. The difference is statistically significant.

Clarida, Galí and Gertler (2000) argue that there was a change in the conduct of monetary policy during Paul Volker's chairmanship at the Federal Reserve. They find statistically significant differences in estimates of a Taylor rule for monetary policy before and after Volker's tenure. Other supporting evidence is presented by Galí, López-Salido and Vallés (2003) who find that the response of hours to a neutral technology shock before Volker is different from after that time. They estimate hours drop for several quarters after a neutral technology shock in the pre-Volker period, but using data in the Volker-Greenspan era they rise. Consistent with Clarida, *et. al.* (2000), they interpret these findings as arising from an increased emphasis on price stability at the Fed during the Volker-Greenspan period.

Stock and Watson (2002, 2003) document the substantial decline in volatility of many macroeconomic aggregates after 1984. The decline in volatility of residential investment is particularly large. This leads Stock and Watson to speculate that legislation in the early 1980s to reintegrate mortgage markets with other capital markets might have caused structural changes which account for the decline in aggregate volatility. Campbell and Hercowitz (2004) argue that the structure of mortgage contracts has changed since the regulatory changes. They show in a real business cycle model how such changes reduce the amplitude of hours and output responses to neutral technology shocks.

These considerations all suggest that the sample should be split. Under a change in monetary policy or regulatory regime, individual decision rules change, and consequently so do the coefficients in (11). This is also true for the trend-break case, since the Lucas critique applies to structural change due to changes in technology as well to changes in the

[23] The estimate for the baseline real investment price is 1982:IV, for the NIPA-based equipment price is 1982:II, and for the GCV annual equipment price is 1982. Bai-Perron tests of the null of no change in the mean growth of the real price against the alternative of at least one change in this mean are rejected at conventional significance levels with these series.

government's policy rule. Since the point estimate of the trend break in the investment price is near the time of the policy changes and the onset of the decline in aggregate volatility, it is natural to split the sample to accommodate all three factors. Galí, *et. al.'s* (2002) split dates accomplish this: the first sub-sample is 1955:I-1979:II and the second is 1982:III-2000:IV. The limited size of the two sub-samples means that estimating a seven variable system is problematic. Given the potential importance of monetary policy, the nominal interest rate and inflation are included. Consequently, the two nominal expenditure share variables are dropped from the seven variable system, and the resulting five-variable system is considered. This is essentially the system estimated in Galí, *et. al.* (2002) appended to include the investment price.

Figures 8 and 9 display the responses of the real price, labor productivity, hours and output for the two sub-samples. As before, responses to N-shocks in the comparable one-technology model without the investment price are also displayed. Consistent with the structural break hypothesis, there are noticeable differences across the two sub-samples. The differences are the most dramatic with hours. In the first sub-sample, in response to either shock, hours responds by immediately falling, before recovering vigorously and turning positive after about a year. The fall and subsequent increase in hours after both the I- and N-shock are statistically significant. In the second sub-sample, the hours response to an I-shock is hump shaped, and qualitatively similar to the full-sample estimates. The amplitude of this response is clearly lower in the second sub-sample compared to the first, but it is still significant. The two-technology hours response to the N-shock is not significant in the second sub-sample. The other variable to display large differences across sub-samples is the real price. This goes from rising significantly after an N-shock in the first sub-sample to being essentially unresponsive in the second-subsample, which might suggest the economy has become more flexible in factor reallocation. The responses in the first sub-sample suggest the model of section 2.1 might miss something. However, the initial decline in hours in the first sub-sample suggests that productivity should rise initially, as indeed it does for both shocks. Overall, the responses seem broadly consistent with the theoretical model in the second-subsample.

An important difference between the two sub-samples, is the decline in the amplitude of the responses in the second sub-sample compared to the first. This is mostly due to the fact that the shocks are estimated to be much less volatile in the second sub-sample. In the first sub-sample the estimated standard deviations are 0.68% and 1.1% for the I-shock and N-shocks, while in the second subsample they are 0.25% and 0.45%.[24] This decline in the volatility of the two technology shocks helps explain the lower aggregate volatility in the post-1984 period documented by Stock and Watson.

Figure 10 and tables 4-6 show the contribution of technology shocks to short-run fluctuations in the two sub-samples. The historical decompositions of hours in figure 10 confirm the previous findings. I-shocks continue to track the boom of the late 1990s quite closely. Because of the short samples, the business cycle decomposition should be viewed with some caution, especially for the second sub-sample. Table 5 shows that the contribution of technology shocks to the forecast errors of hours are smaller than those in table 3, but are still large. Except for output in the first sub-sample, I-shocks contribute more to the forecast errors than N-shocks. Table 6 shows that for business cycle frequencies, I-shocks are more important than N-shocks. The total contribution of technology shocks to business cycle fluctuations in hours is cut in half in the second sub-sample, but for output it almost doubles.

To conclude, under the structural-break hypothesis the same main results emerge as with estimation over the full sample: technology shocks are important for short run fluctuations and investment-specific shocks matter more than neutral shocks. By splitting the sample, a new finding also emerges. Namely, the post-1984 decline in aggregate volatility is at least partly due to a decline in the volatility of the two technology shocks.

[24]For the full sample the standard deviation of the I-shock is 0.99% and for the N-shock is 0.51%.

6. Other Approaches to Including Hours in the Analysis

The previous section reports findings using the baseline data set, in which hours are measured by the level of per capita non-farm business hours. Per capita hours have some low frequency variation, and there is little agreement in the literature about how to deal with this. As discussed by Galí and Rabanal (2004), a key result depends on how the low frequency movements are addressed. If hours are included in levels and shocks are identified under the one-technology assumption, then hours tend to respond positively to an N-shock. If hours are included in first-differences, then hours tend to respond negatively. In both cases labor productivity responds positively. If hours respond negatively to a shock which raises labor productivity, then the technology shock view of business cycles is seriously challenged. While the hours response to an N-shock depends on how hours are included, the conclusion that N-shocks have small short run effects does not. This section argues that the main findings here are similarly robust to how hours are included.

Four transformations of per capita hours and two measures of total hours are considered. The four transformations are log levels, first differences, quadratic detrending, and an adjustment to account for government purchases. Christiano, *et. al.* (2004) argue for the levels specification over the alternatives. The first difference specification is considered by several authors, including Francis and Ramey (2003) and Galí and Rabanal (2004). Galí and Rabanal (2004) also consider quadratic detrending. The government spending adjustment is motivated by Francis and Ramey (2004), and is discussed below. Total hours are measured by the Bureau of Labor Statistics' (BLS) non-farm business and private business hours series, both of which have been considered in the literature.[25] When the latter hours

[25] Non-farm hours might be a more reliable measure of hours because private business hours is affected by measurement bias in the early part of the sample. Per capita private business hours, which include the farm sector, drifts down from 1947 to the early 1960s, but there is hardly any drift in non-farm hours. This difference is due to the surveys underlying farm and non-farm hours. Primarily, farm hours is based on a household survey and non-farm hours is based on a survey of establishments. As discussed by Eldridge, Manser and Otto (2003, pp.3-4), measures of hours worked are biased upward in the household survey compared to the establishment survey. As the farm sector's employment share has declined, the share of private business hours measured using the household survey has also declined, leading to an apparant secular decline in private business hours' measurement bias.

measure is used, the corresponding measures of productivity and output are substituted for their baseline counterparts.

Francis and Ramey (2004) argue that various demographic, economic and social trends induce non-stationarity in per capita hours. Real business cycle models do not take this into account, which leads Francis and Ramey to consider several adjustments to per capita hours. One adjustment addresses the fact that both BLS measures of hours exclude the government. Francis and Ramey use a version of section 2.1's model with exogenous government spending to show that hours devoted to producing goods for the government acts like a drain on the time endowment of the representative agent. They use this to argue for a particular adjustment to per capita hours. This section considers the government adjustment because it is fits naturally into the paper's theoretical framework.[26]

To conserve on space, this section focuses on point estimates of the hours responses only, in figures 11-13, and the business cycle decompositions of hours and output, in tables 7-9. In results not reported, the forecast error decompositions lead to conclusions similar to the business cycle decompositions. The first-difference private business specification of the seven-variable model is explosive. So, for this case, there is no response for hours in figure 11 and there are no entries in table 7. The figures and tables indicate that the findings with the full sample estimates depend somewhat on the way hours are included, but when the sample is split there is much less dependence.

Figure 11, based on the full sample, shows that the log levels and government adjustment cases are similar, but that differences emerge when hours are first-differenced or quadratically detrended. With private business hours, the relative magnitude of responses to I-shocks and N-shocks is reversed. In contrast to the previous literature, the hours responses are mostly positive, although sometimes with a delay. Figures 12 and 13 show that most of the differences just described disappear when the sample is split. The levels and government adjustment specifications are still the closest, but now most of the other transformations

[26] Francis and Ramey (2004) also consider adjustments for rates of school attendance and the labor force participation of the elderly. This section does not consider these adjustments since it is not as obvious how to incorporate such life-cycle considerations into my infinite horizon model.

imply responses similar to these. The biggest differences are in the second sub-sample, where the response to an I-shock with quadratic detrending, and to an N-shock with first-differencing, are outliers.

There are two key observations to make from the tables. First, the total contribution of technology shocks to the business cycle is generally large when the sample is split. For non-farm hours, all the split sample specifications imply a large combined technology contribution for hours and usually for output as well. With private business hours, the business cycle contributions are similar to the baseline when the sample is split. Over the full sample, private business hours suggest a weaker role for technology shocks than the baseline. Second, more often than not, I-shocks are more important for the business cycle than N-shocks when the sample is split. The main exception is for the quadratic specifications in the second sub-sample. One reason to discount these last results is that the quadratic specification implies hours worked are only marginally above trend in the latter half of the 1990s.

These findings suggest the conclusion that technology shocks play a key role in short-run fluctuations is robust to how hours are included in the analysis if the sample is split.[27] The same is true for the conclusion that I-shocks are more important than N-shocks. These findings might be viewed as further evidence in favor of splitting the sample.

7. Are the Shocks Technology?

This section assesses the plausibility of the identified technology shocks by subjecting them to additional tests. Francis and Ramey (2003), following Evans (1992), propose examining the quality of technology shocks by testing whether other variables Granger-cause them. If the shocks are truly due to exogenous technological innovations, then other variables should not predict them. This section 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

[27] Gali (2004) displays results on the contribution of I-shocks and N-shocks based on a three variable system estimated over the full sample, including non-farm business hours in first-differences, and not imposing assumption 3. He finds smaller short run effects of technology shocks than those reported here.

capital tax rate Granger-cause the baseline identified technology shocks. The first three variables are included because they are commonly associated with short run fluctuations. The fourth variable is included since theory predicts that such changes might have affects on labor productivity and the real investment price. In a version of section 2.1's model with a proportional capital income tax, a permanent increase in the capital 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. Since average capital taxes vary a lot over the sample period, it is possible that the identified shocks reflect permanent movements in capital taxes.

Table 10 reports marginal probabilities associated with F-tests, each based on a regression of the indicated technology shock on a constant and current 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 of 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.

The table indicates that in only two cases is the null hypothesis of no Granger-causality rejected at the 5% percent significance level. It is never rejected for the capital tax and the Federal Funds rate. Granger causality is marginally rejected at the 5% level for the oil dates on the I-shocks in the second subsample, and at the 1% level for military spending on N-shocks in the full sample. The oil shock result might not be surprising. Suppose an exogenous increase in the price of oil induces substitution toward equipment which the US 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, an oil shock is very much like an I-shock. The military spending result is overturned when the sample is split. This might be another reason to prefer the split sample findings.

8. Conclusion

This paper argues that, by taking into account investment-specific technical change, previous findings which suggest technology shocks are unimportant for short run fluctuations, are overturned. Neutral and investment-specific technology shocks combined account for 40-60 percent of the business cycle variation in hours and output, and for more than 50% of the forecast error in these variables over an eight year horizon. The majority of these effects are due to the investment-specific shock. When the sample is split to account for a change in the average growth of the investment-specific technology and changes in policy, these main findings are confirmed. The technology shocks are much less variable in the second half of the sample, which helps to explain the decline in aggregate volatility in the post-1984 period.

Since the results are based on a procedure which abstracts from transitory technology shocks, they should be viewed as representing a lower bound on the overall contribution of technology shocks to short run fluctuations. Therefore, the results strongly suggest that technology shocks, or more generally, shocks to the efficiency of producing goods, are important for understanding short run fluctuations. Since investment-specific shocks account for the majority of the effects, business cycle research might benefit from being directed toward studying these shocks and other factors which influence the efficiency of producing investment goods but not consumption goods.

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9. Appendix

This appendix describes the data, derives the linear restriction associated with assumption 3, and describes some results based on using different measures of the real investment price.

9.1. The Data

Since the GCV equipment deflator is an annual series, it must be interpolated. There is no generally agreed on method of interpolation. This paper uses 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.[28]

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 derived by using the NIPAs chain-weighting procedure to combine the GCV equipment-specific deflator with the NIPA deflators for non-residential 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 which 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 1947-1983 and this is spliced to the NIPA deflator for the remaining years of the sample. In the last few years where 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 where it is relevant, the data codes from the Haver Analytics Database where the series was obtained are displayed in parenthesis. To be consistent with the GCV equipment deflator, the NIPA series are those prior to the 2004 revisions, available as of October, 2002.

- Nominal consumption is nondurables consumption (CN) plus services consumption (CS) plus government consumption (the sum of GFDE, GFNE and GSE) plus the service flow from consumer durables (chain-weighted real service flow obtained from David

[28] 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`

Reifschneider at the Board of Governors, converted to nominal terms with the price index for durable consumption goods described above, where the NIPA durables deflator is CD/CDH). Real consumption is the chain-weighted sum of the components of nominal consumption using the deflators for nondurables consumption (CN/CNH), services consumption (CS/CSH), chain-weighted government consumption (the price indexes for the components of government consumption are GFDE/GFDEH, GFNE/GFNEH, GSE/GSEH). The consumption deflator is the ratio of nominal to real consumption.

- Per-capita non-farm hours is non-farm business hours (LXNFH) divided by the non-institutional 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). Per-capita private business hours is private business hours (LXBH) divided by the non-institutional civilian population 16 years and over.

- Nominal non-farm business output is non-farm business output (LXNFO) multiplied by the deflator for that output (LXNFI). Non-farm business labor productivity in consumption units is non-farm labor productivity (LXNFA) multiplied by the deflator for non-farm business output (LXNFI) divided by the consumption deflator. Nominal private business output is private business output (LXBO) multiplied by the deflator for that output (LXBI). Private business labor productivity in consumption units is private labor productivity (LXBA) multiplied by the deflator for non-farm business output (LXBI) divided by the consumption deflator.

- Nominal total investment is private non-residential structures investment (FNS) plus private equipment investment (FNE) plus private residential structures investment (FR) plus expenditures on consumer durables (CD) and government investment (the sum of GFDI, GFNI and GSI). Real total investment is the chain-weighted sum of the components of nominal total investment using the deflators for non-residential structures (FNS/FNSH), the GCV equipment deflator described above, residential structures (FR/FRH), the durables consumption deflator described above, and chain-weighted government investment (the price indexes for the components of government investment are GFDI/GFDIH, GFNI/GFNIH, GSI/GSIH). The total investment deflator is the ratio of nominal to real total investment. 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 NIPA equipment deflator is nominal equipment expenditures (FNE) divided by real equipment expenditures (FNEH). The NIPA consumption deflator is the same as the consumption deflator described above except that the consumer durables price index is taken from the NIPA (CD/CDH). The NIPA total investment deflator is the same as the baseline total investment deflator except the equipment and consumer durables deflators are replaced with their NIPA counterparts.

- The interest rates used are the Federal funds rate (FFED) and the yield on 3-month Treasury Bills (FTBS3).

- The Ramey and Francis (2004) government adjustment is calculated by the author according to the steps described in the appendix to that paper. The capital tax series is from Burnside, Eichenbaum and Fisher (2003).

9.2. Restricting Labor Productivity's Response to an I-Shock

Recall the moving average representation of the model is

$$\begin{aligned} y_t &= \Phi(L)\varepsilon_t && (16) \\ &= C(L)^{-1}\varepsilon_t, && (17) \end{aligned}$$

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

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

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

Let the ij'th element of $C(1)$ be denoted c_{ij}. Recall that the ij'th 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 ji'th 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

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

It follows that assumption 3 holds if and only if

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

9.3. Other measures of the real investment price

This section investigates the implications of using the GCV-based total investment, NIPA equipment and NIPA total investment deflators. A complete set of results is available from the author upon request. Mirroring other results in the paper, some differences emerge when the seven-variable system is estimated using the alternative price measures over the full sample, but most of these differences disappear when the sample is split.

Over the full sample, the combined effects of the two technology shocks are smaller. For example, technology shocks account for 41% and 37% of the business cycle volatility of hours and output with the baseline measure of the real price, but with the NIPA equipment measures the estimated contributions are only 16% and 22%. The differences in the forecast errors are much less pronounced for the total effects of technology. For the NIPA equipment series, the N-shocks matter more than I-shocks.

When the sample is split the differences with the baseline results essentially disappear, with one exception. In the first sub-sample using the NIPA equipment series, N-shocks matter more than I-shocks. However, the total contribution of technology shocks is similar to that for the GCV equipment series. The usual results continue to hold with the NIPA equipment series in the second subsample.

These findings are explained as follows. As discussed in section 4.1, at the annual frequency, the GCV series incorporates all the component NIPA deflators which are already quality adjusted by the BEA. Only those component deflators which have not already been quality adjusted by the BEA are estimated by Cummins and Violante. The biggest differences between the NIPA- and GCV-based series are before 1980, when the share of investment that the BEA quality adjusts is small. Therefore, over the full sample, the average quality bias is not constant. When the sample is split, however, the bias is much closer to being constant within the two subsamples. This explains why the NIPA and GCV results are much closer when the sample is split than over the full sample.

Finally, if the NIPA equipment deflator is used to measure the real investment price, the second sub-sample can be extended to 2004:IV. When this is done the findings for the second sub-sample are almost identical to those based on the shorter sample.

Table 1. Forecast Error Decompositions in the Three Variable Model, 1955:I-2000:IV

	Hours			Output		
Horizon	All Technology	Investment	Neutral	All Technology	Investment	Neutral
1	**0.28**	**0.25**	**0.03**	**0.89**	**0.16**	**0.73**
	(0,0.53)	(0,0.50)	(0,0.06)	(0.79,1)	(0,0.32)	(0.49,1)
4	**0.54**	**0.46**	**0.09**	**0.88**	**0.33**	**0.56**
	(0.24,0.97)	(0.08,0.90)	(0,0.17)	(0.78,1)	(0,0.64)	(0.15,0.91)
8	**0.67**	**0.55**	**0.12**	**0.94**	**0.35**	**0.58**
	(0.43,1)	(0.23,1)	(0,0.24)	(0.88,1)	(0.02,0.69)	(0.21,0.91)
12	**0.71**	**0.57**	**0.14**	**0.95**	**0.35**	**0.61**
	(0.50,1)	(0.26,1)	(0,0.26)	(0.91,1)	(0.04,0.67)	(0.26,0.93)
16	**0.73**	**0.58**	**0.14**	**0.96**	**0.33**	**0.63**
	(0.52,1)	(0.27,1)	(0.0.27)	(0.93,1)	(0.03,0.65)	(0.29,0.95)
32	**0.74**	**0.59**	**0.15**	**0.98**	**0.32**	**0.66**
	(0.54,1)	(0.28,1)	(0,0.28)	(0.96,1)	(0,0.62)	(0.35,0.99)

Table 2. Business Cycle Effects of Technology Shocks, 1955:I-2000:IV

	Three Variable Model			Seven Variable Model		
Statistic	All Technology	Investment	Neutral	All Technology	Investment	Neutral
$\sigma^2_{H^m}/\sigma^2_{H^d}$	**0.68**	**0.55**	**0.07**	**0.41**	**0.42**	**0.03**
	(0.39,1)	(0.20,1)	(0,0.10)	(0.06,0.70)	(0.21,0.80)	(0,0.04)
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	**0.79**	**0.42**	**0.31**	**0.37**	**0.27**	**0.15**
	(0.54,1)	(0.11,0.79)	(0,0.46)	(0,0.59)	(0.11,0.51)	(0,0.28)

Table 3. Forecast Error Decompositions in the Seven Variable Model, 1955:I-2000:IV

	Hours			Output		
Horizon	All Technology	Investment	Neutral	All Technology	Investment	Neutral
1	**0.30**	**0.31**	**0.00**	**0.48**	**0.03**	**0.44**
	(0.17,0.60)	(0.26,0.61)	(0,0)	(0.31,0.84)	(0,0.07)	(0.27,0.82)
4	**0.57**	**0.54**	**0.02**	**0.63**	**0.23**	**0.40**
	(0.42,1)	(0.53,1)	(0,0.04)	(0.46,1)	(0.09,0.45)	(0.07,0.76)
8	**0.60**	**0.55**	**0.05**	**0.62**	**0.16**	**0.45**
	(0.44,1)	(0.50,1)	(0,0.08)	(0.41,0.97)	(0,0.31)	(0.14,0.80)
12	**0.58**	**0.49**	**0.09**	**0.65**	**0.11**	**0.54**
	(0.40,0.94)	(0.40,0.94)	(0,0.16)	(0.46,0.99)	(0,0.21)	(0.29,0.88)
16	**0.58**	**0.45**	**0.13**	**0.69**	**0.08**	**0.61**
	(0.40,0.91)	(0.33,0.87)	(0,0.24)	(0.53,1)	(0,0.16)	(0.40,0.97)
32	**0.67**	**0.49**	**0.17**	**0.81**	**0.09**	**0.72**
	(0.51,0.93)	(0.38,0.96)	(0,0.29)	(0.70,1)	(0,0.17)	(0.56,1)

Table 4. Forecast Error Decompositions in the Five Variable Model, 1955:I-1979:II

	Hours			Output		
Horizon	All Technology	Investment	Neutral	All Technology	Investment	Neutral
1	**0.44**	**0.29**	**0.16**	**0.15**	**0.03**	**0.12**
	(0.14,0.87)	(0.01,0.58)	(0,0.31)	(0,0.29)	(0,0.06)	(0,0.24)
4	**0.39**	**0.24**	**0.15**	**0.09**	**0.04**	**0.05**
	(0.09,75)	(0,0.47)	(0,0.30)	(0,0.15)	(0,0.07)	(0,0.10)
8	**0.35**	**0.20**	**0.14**	**0.34**	**0.14**	**0.20**
	(0.03,0.62)	(0,0.39)	(0,0.28)	(0,0.57)	(0,0.26)	(0,0.38)
12	**0.39**	**0.25**	**0.15**	**0.58**	**0.26**	**0.32**
	(0.12,0.69)	(0,0.47)	(0,0.28)	(0.38,1)	(0,0.51)	(0,0.61)
16	**0.43**	**0.28**	**0.14**	**0.68**	**0.31**	**0.37**
	(0.16,0.75)	(0,0.53)	(0.0.28)	(0.51,1)	(0,0.59)	(0.04,0.71)
32	**0.45**	**0.30**	**0.15**	**0.79**	**0.34**	**0.45**
	(0.15,0.78)	(0,0.58)	(0,0.28)	(0.67,1)	(0,0.66)	(0.09,0.86)

Table 5. Forecast Error Decompositions in the Five Variable Model, 1982:III-2000:IV

	Hours			Output		
Horizon	All Technology	Investment	Neutral	All Technology	Investment	Neutral
1	**0.03**	**0.03**	**0.002**	**0.84**	**0.02**	**0.82**
	(0,0.06)	(0,0.07)	(0,0.01)	(0.70,1)	(0,0.04)	(0.69,1)
4	**0.13**	**0.06**	**0.07**	**0.69**	**0.16**	**0.53**
	(0,0.22)	(0,0.11)	(0,0.13)	(0.45,1)	(0,0.31)	(0.25,0.99)
8	**0.26**	**0.19**	**0.06**	**0.76**	**0.34**	**0.42**
	(0,0.46)	(0,0.37)	(0,0.12)	(0.57,1)	(0,0.66)	(0.07,0.79)
12	**0.40**	**0.34**	**0.05**	**0.83**	**0.49**	**0.34**
	(0,0.68)	(0,0.65)	(0,0.10)	(0.70,1)	(0.21,0.90)	(0,0.60)
16	**0.45**	**0.39**	**0.06**	**0.84**	**0.57**	**0.27**
	(0.07,0.76)	(0,0.73)	(0.0.11)	(0.72,1)	(0.35,1)	(0,0.46)
32	**0.52**	**0.46**	**0.06**	**0.90**	**0.65**	**0.25**
	(0.17,0.86)	(0.09,0.84)	(0,0.11)	(0.82,1)	(0.46,1)	(0,0.41)

Table 6. Business Cycle Effects of Technology Shocks in the Five Variable Model with a Break in the Sample

Statistic	All Technology	Investment	Neutral
		Panel A: 1955:I-1979:II	
$\sigma^2_{H^m}/\sigma^2_{H^d}$	**0.73**	**0.47**	**0.21**
	(0.59,1)	(0.22,0.92)	(0,0.39)
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	**0.44**	**0.42**	**0.08**
	(0.12,0.83)	(0.22,0.83)	(0,0.13)
		Panel B: 1982:III-2000:IV	
$\sigma^2_{H^m}/\sigma^2_{H^d}$	**0.38**	**0.36**	**0.15**
	(0,0.66)	(0,0.64)	(0,0.22)
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	**0.80**	**0.67**	**0.33**
	(0.32,1)	(0.43,1)	(0,0.59)

Table 7. Business Cycle Effects of Technology Shocks in the Seven Variable Model for Various Ways of Modelling Hours, 1955:I-2000:IV

Statistic	Non-Farm Business Hours: All Technology	Non-Farm Business Hours: Investment	Non-Farm Business Hours: Neutral	Private Business Hours: All Technology	Private Business Hours: Investment	Private Business Hours: Neutral
			Log-Levels			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.41	0.42	0.03	0.14	0.10	0.09
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.37	0.27	0.15	0.23	0.11	0.18
			First-Differences(i)			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.32	0.10	0.17	*	*	*
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.45	0.05	0.35	*	*	*
			Quadratic			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.21	0.16	0.04	0.09	0.04	0.04
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.12	0.13	0.03	0.06	0.04	0.02
			Francis and Ramey (2004) Government Spending Adjustment			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.27	0.25	0.05	0.09	0.06	0.04
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.19	0.19	0.04	0.15	0.07	0.11

Notes: (i) In these specifications A4 need not be imposed explicitly for nonfarm business hours since productivity after an I-shock turns positive before 8 years. The (*) for private business hours indicates the linear model for which A3 is imposed is non-stationary and so is inadmissible. Note that the nonfarm business hours estimates yield extremely persistent responses and both technologies have large permanent effects on hours.

Table 8. Business Cycle Effects of Technology Shocks in the Five Variable Model for Various Ways of Modelling Hours, 1955:I-1979:II

	Non-Farm Business Hours			Private Business Hours		
Statistic	All Technology	Investment	Neutral	All Technology	Investment	Neutral
			Log-Levels			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.73	0.47	0.21	0.81	0.61	0.14
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.44	0.42	0.08	0.61	0.56	0.06
			First-Differences			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.28	0.17	0.10	0.25	0.17	0.08
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.12	0.10	0.03	0.11	0.11	0.02
			Quadratic			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.73	0.08	0.67	0.69	0.15	0.53
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.38	0.07	0.32	0.38	0.12	0.25
			Francis and Ramey (2004) Government Spending Adjustment			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.67	0.26	0.38	0.69	0.53	0.11
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.37	0.25	0.14	0.49	0.48	0.04

Table 9. Business Cycle Effects of Technology Shocks in the Five Variable Model for Various Ways of Modelling Hours, 1982:III-2000:IV

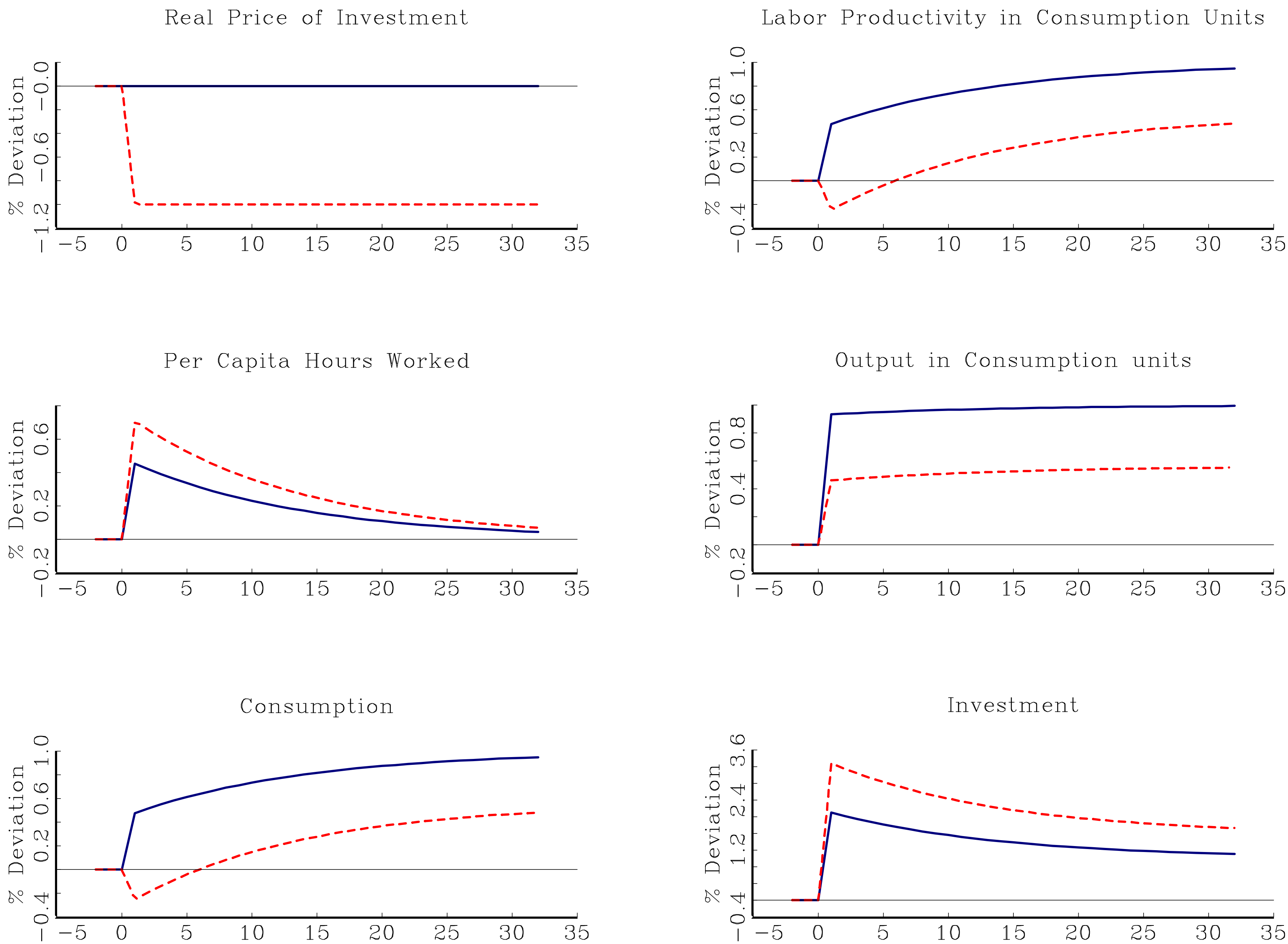
	Non-Farm Business Hours			Private Business Hours		
Statistic	All Technology	Investment	Neutral	All Technology	Investment	Neutral
			Log-Levels			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.38	0.36	0.15	0.47	0.42	0.18
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.80	0.67	0.33	0.99	0.84	0.32
			First-Differences			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.38	0.32	0.20	0.38	0.36	0.10
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.65	0.57	0.24	0.75	0.63	0.20
			Quadratic			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.25	0.23	0.39	0.26	0.24	0.44
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.67	0.41	0.59	0.58	0.40	0.66
			Francis and Ramey (2004) Government Spending Adjustment			
$\sigma^2_{H^m}/\sigma^2_{H^d}$	0.36	0.33	0.16	0.40	0.36	0.19
$\sigma^2_{Y^m}/\sigma^2_{Y^d}$	0.77	0.61	0.35	0.87	0.71	0.33

Table 10. Granger-Causality Tests

Technology Shock	Capital Tax Changes	Federal Funds Rate	Hoover-Perez Oil Dates	Military Spending Changes
	Panel A: 1955:I 2000:IV			
Investment-Specific	0.10	0.99	0.30	0.96
Neutral	0.09	0.73	0.53	0.01
	Panel B: 1955:I-1979:II			
Investment-Specific	0.07	0.93	0.046	0.17
Neutral	0.82	0.82	0.15	0.23
	Panel C: 1982:III-2000:IV			
Investment-Specific	0.55	0.97	*	0.14
Neutral	0.17	0.91	*	0.42

Note: The table reports probabilities 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, where no current value is included. The null hypothesis is that all of the coefficients on the variable in question are jointly equal to zero. The asterisks denote that there are not enough observations of the variable in question to compute a meaningful test.

Figure 1: Theoretical Responses to Investment-Specific and Neutral Technology Shocks



Note: Solid lines - Respones to neutral shock; Dashed lines - Responses to investment-specific shock

Figure 2: Two Measures of Nominal and Real Investment Prices

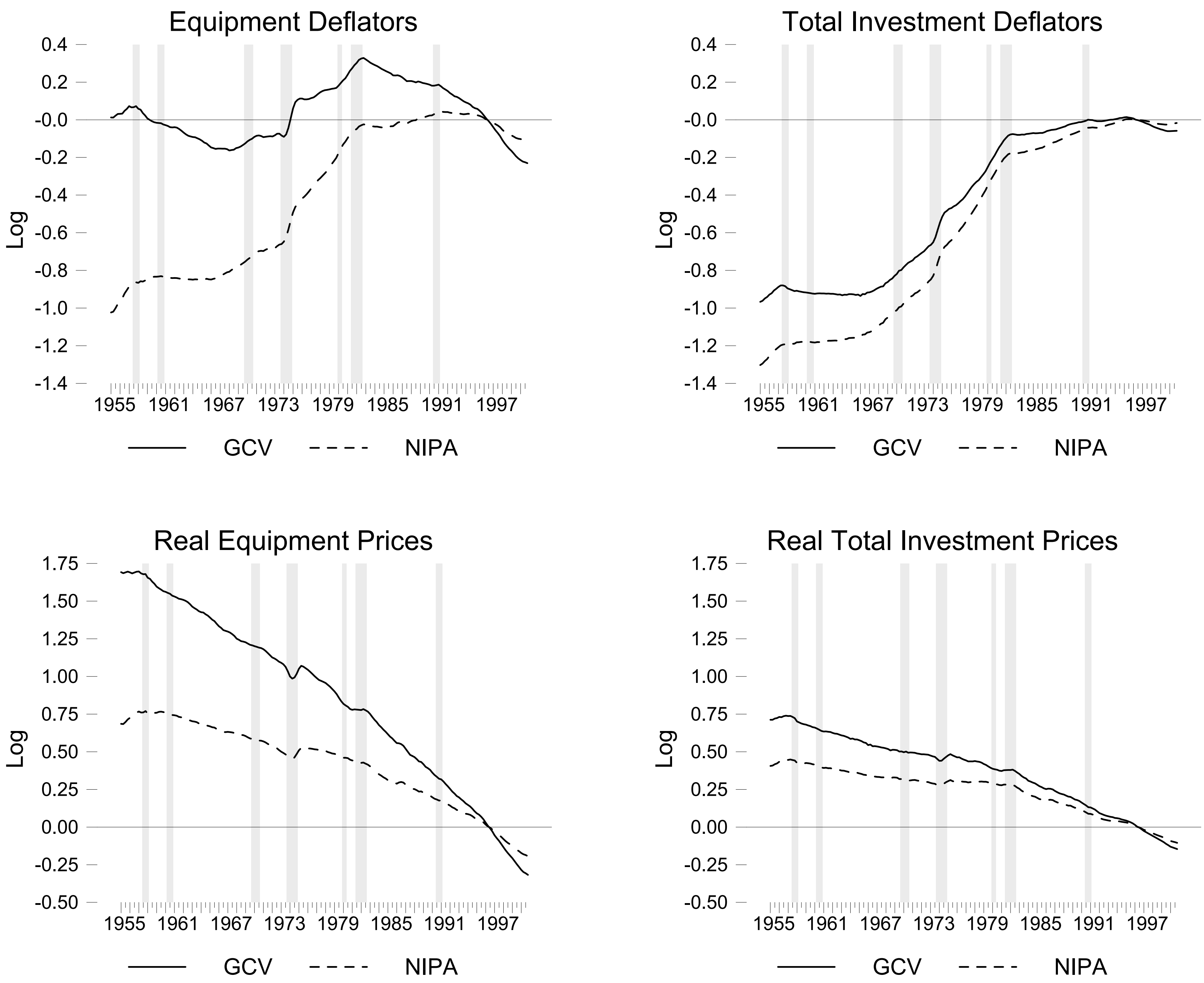
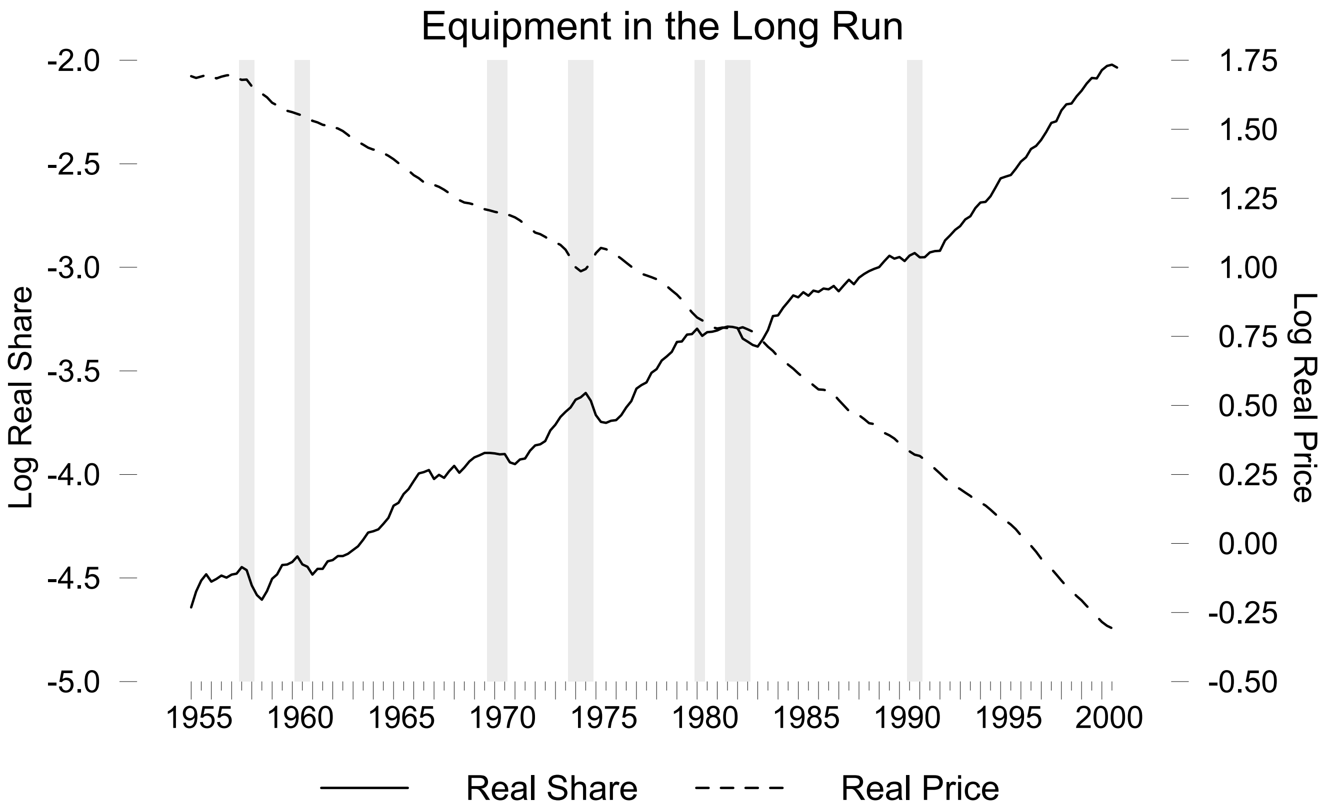


Figure 3: Real Equipment Prices in the Long Run and over the Business Cycle



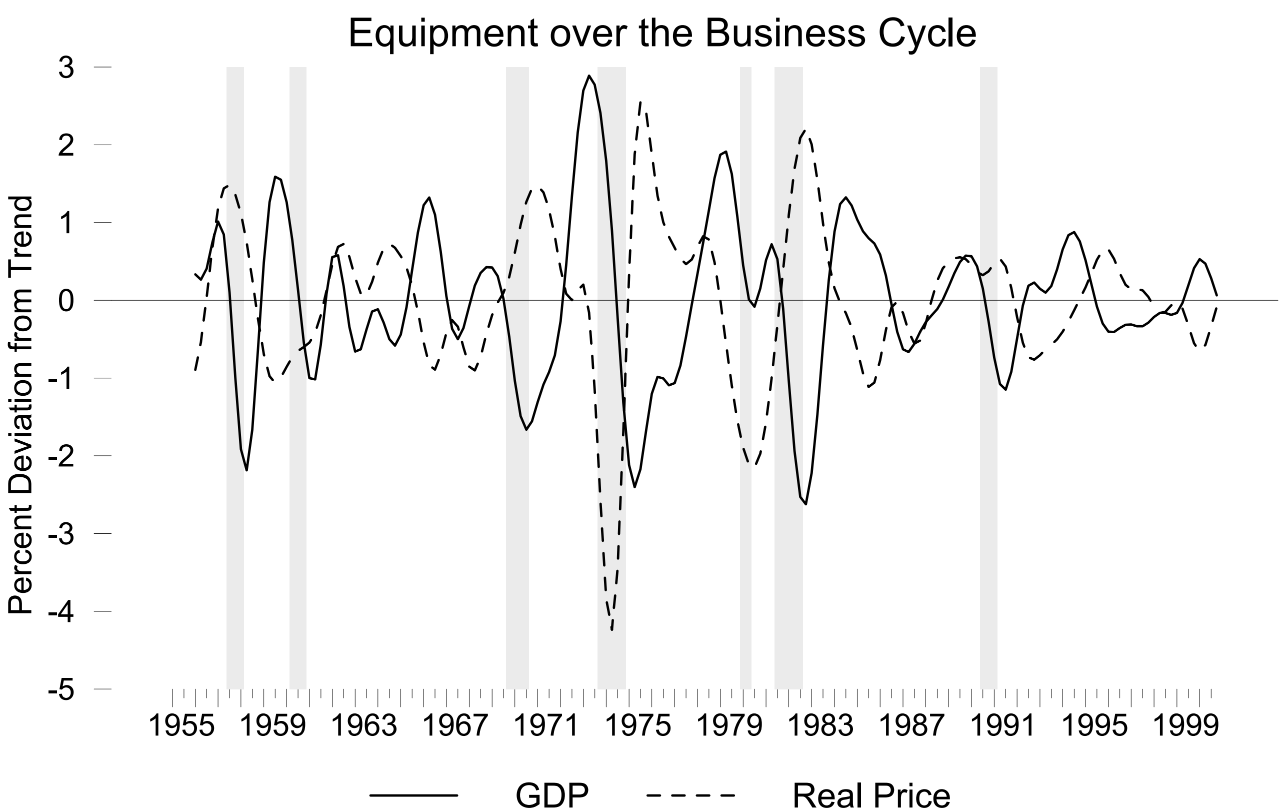
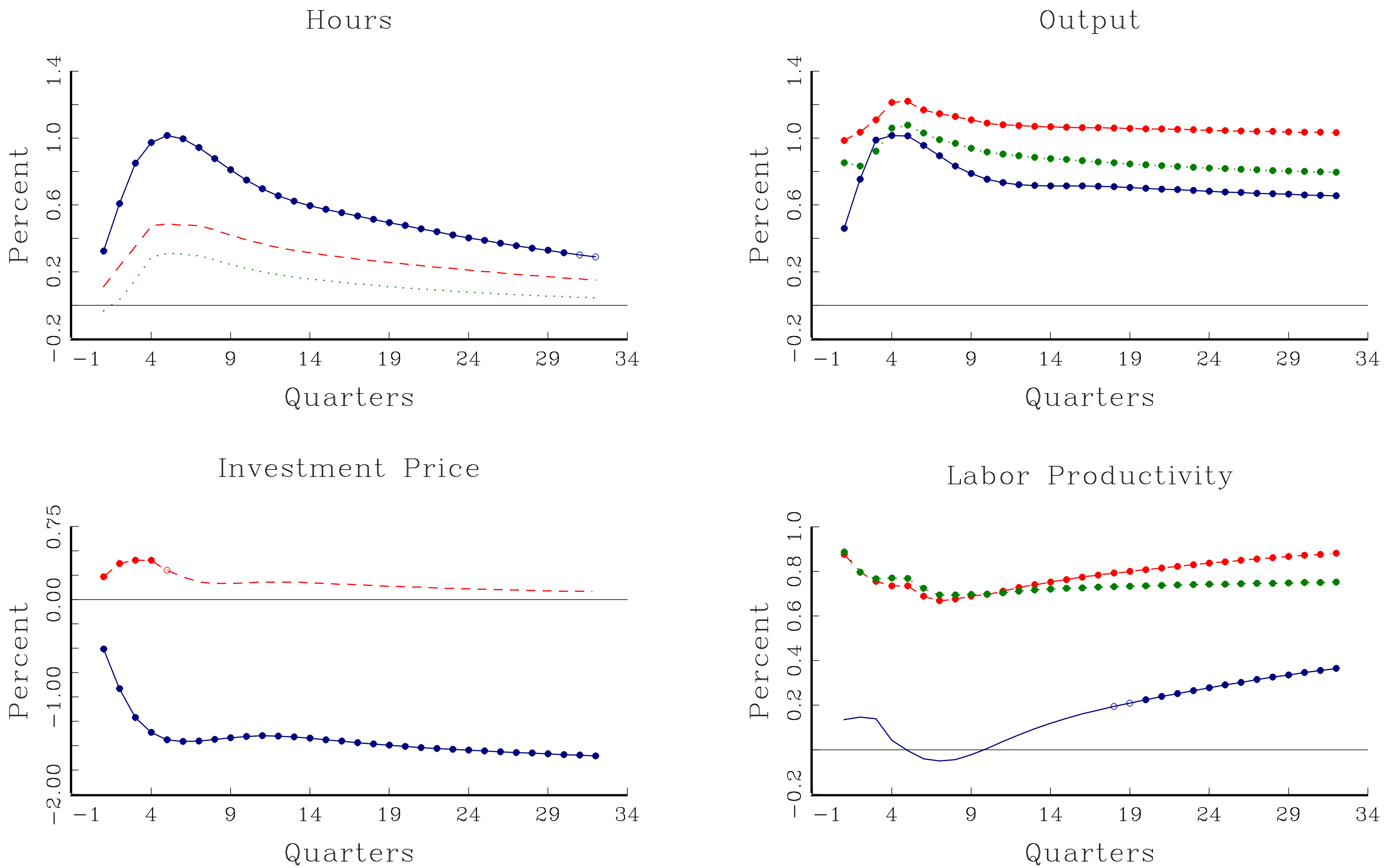
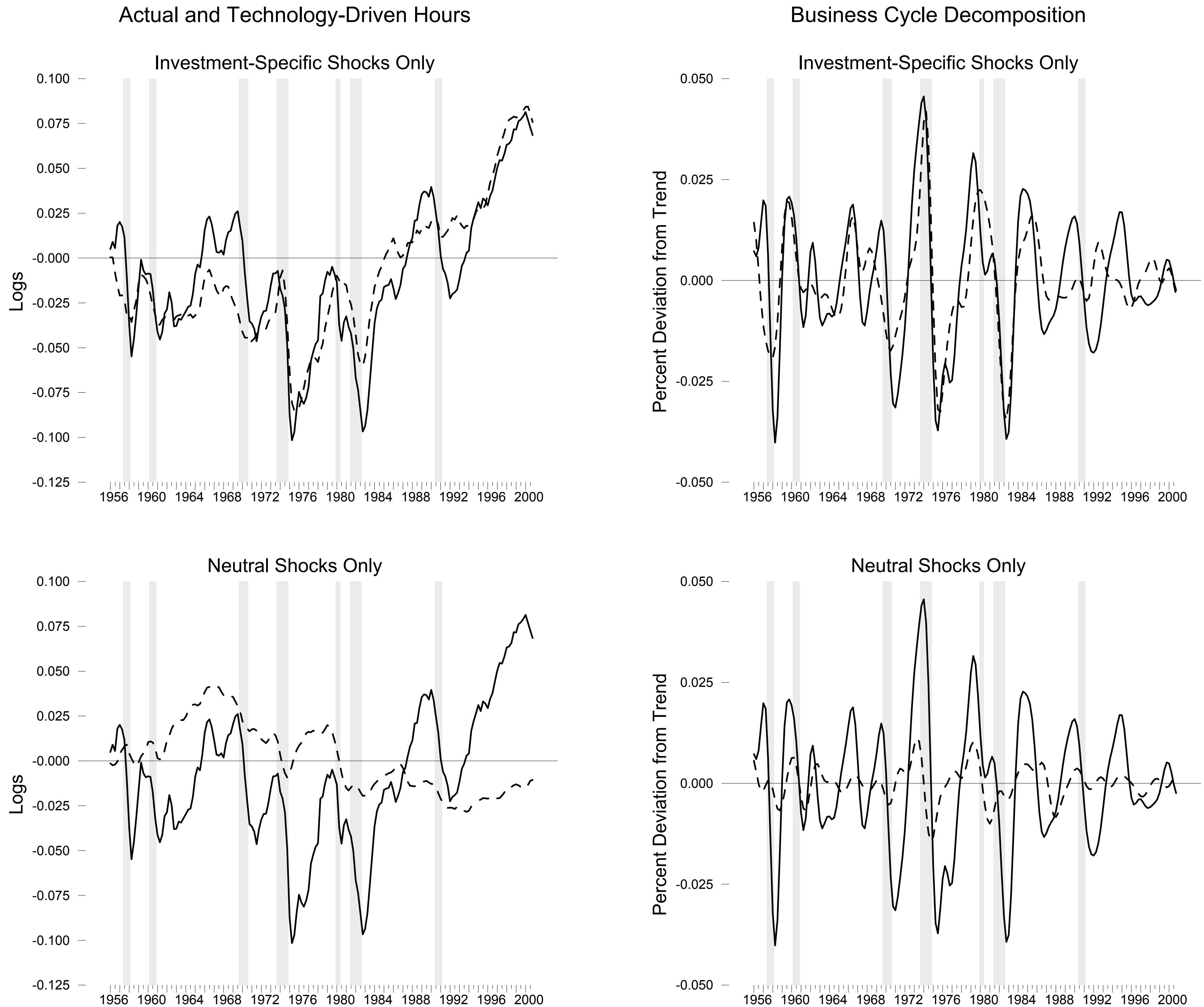


Figure 4: Responses to technology shocks in the two- and three-variable systems



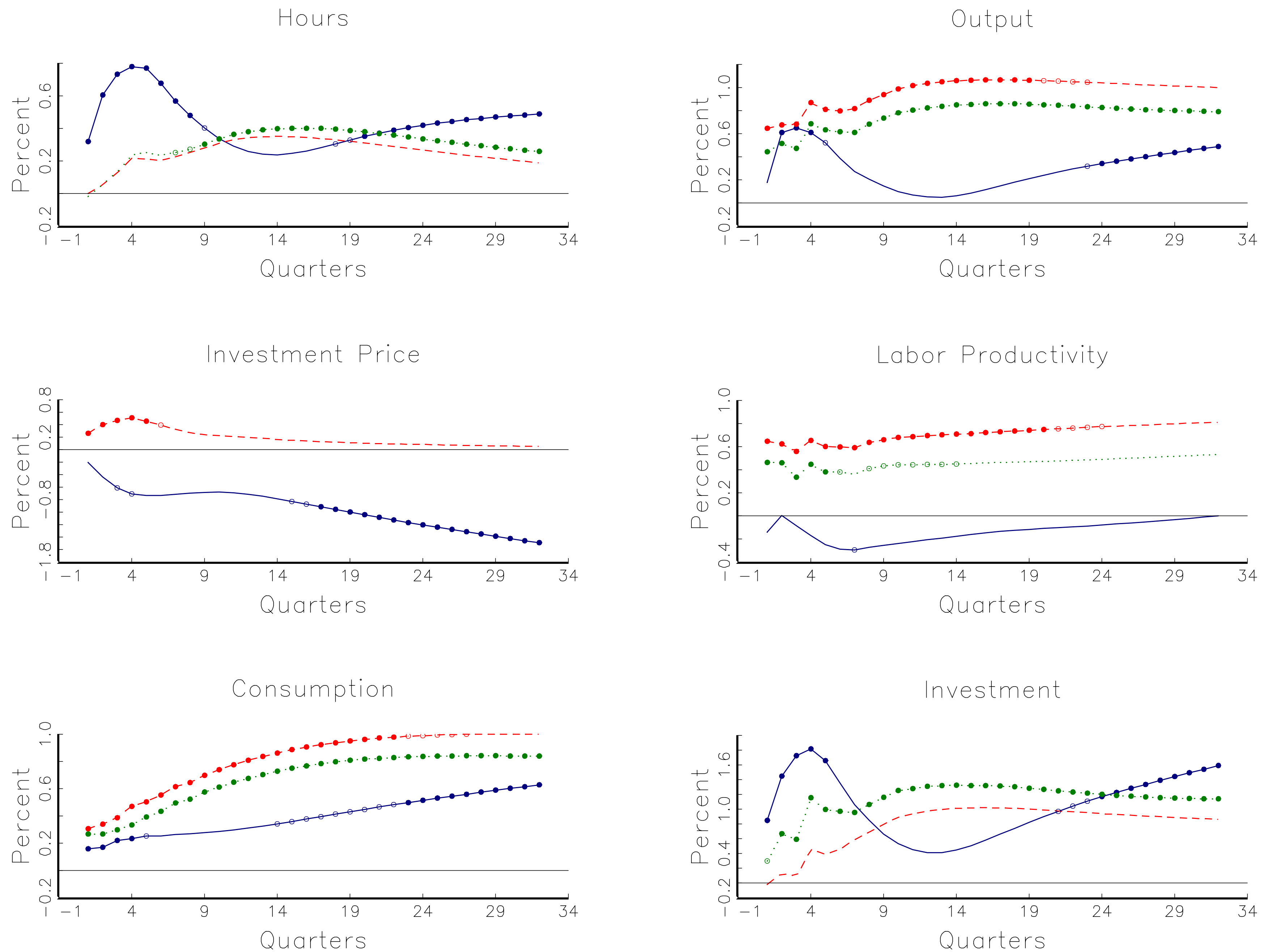
Notes: Solid lines - Respones to I-shocks in the three-variable system; Dashed lines - Respones to N-shocks in the three-variable system; Dotted lines - Responses to N-shocks in the two-variable system; Solid circles indicate the response is significant at the 5% level; Open circles indicate the response is significant at the 10% level.

Figure 5: Decomposing the contribution of technology shocks to hours in the three-variable system



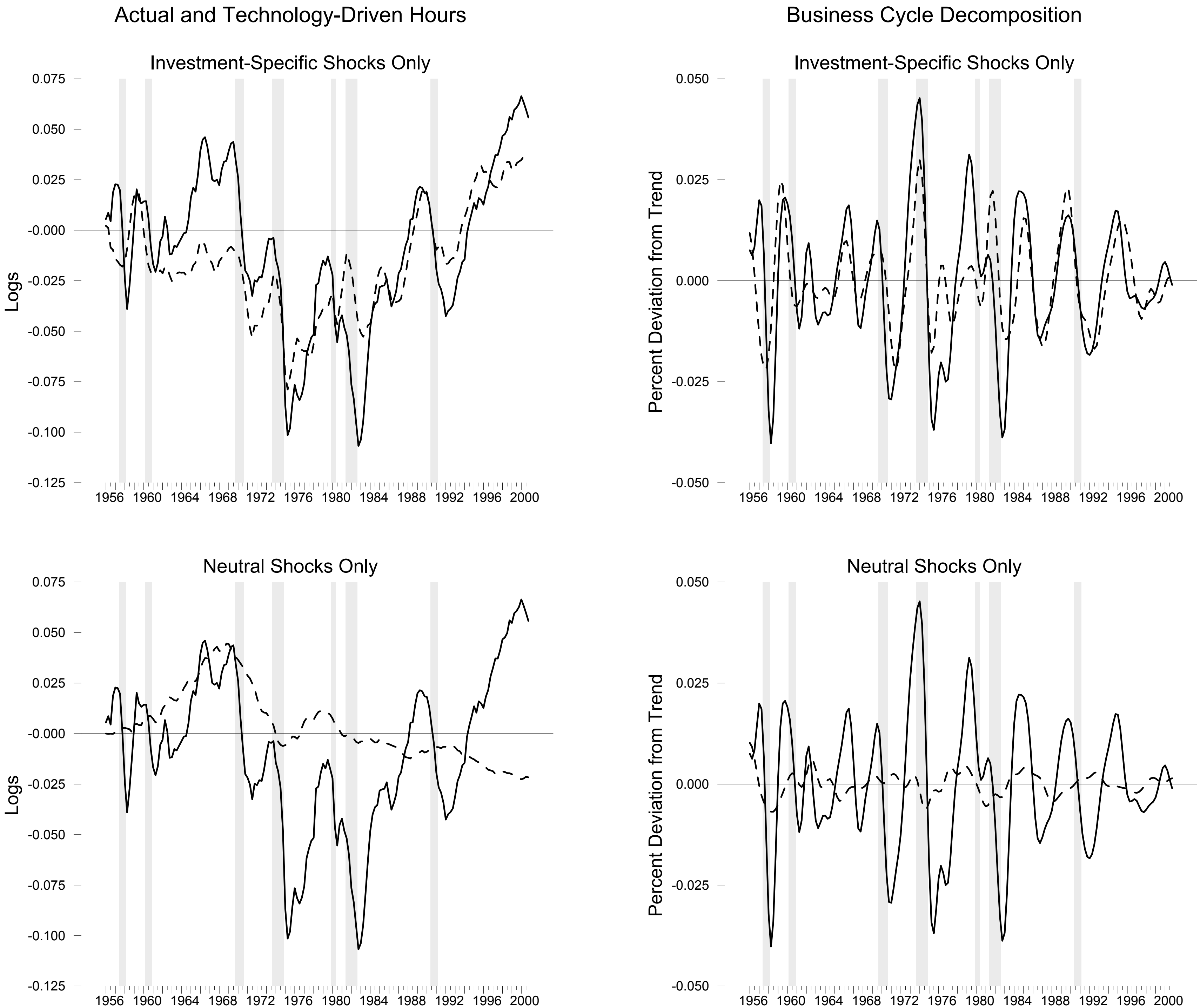
Notes: Solid lines - non-farm business hours; Dashed lines - hours due to the indicated technology shocks

Figure 6. Responses to technology shocks in the six- and seven-variable systems



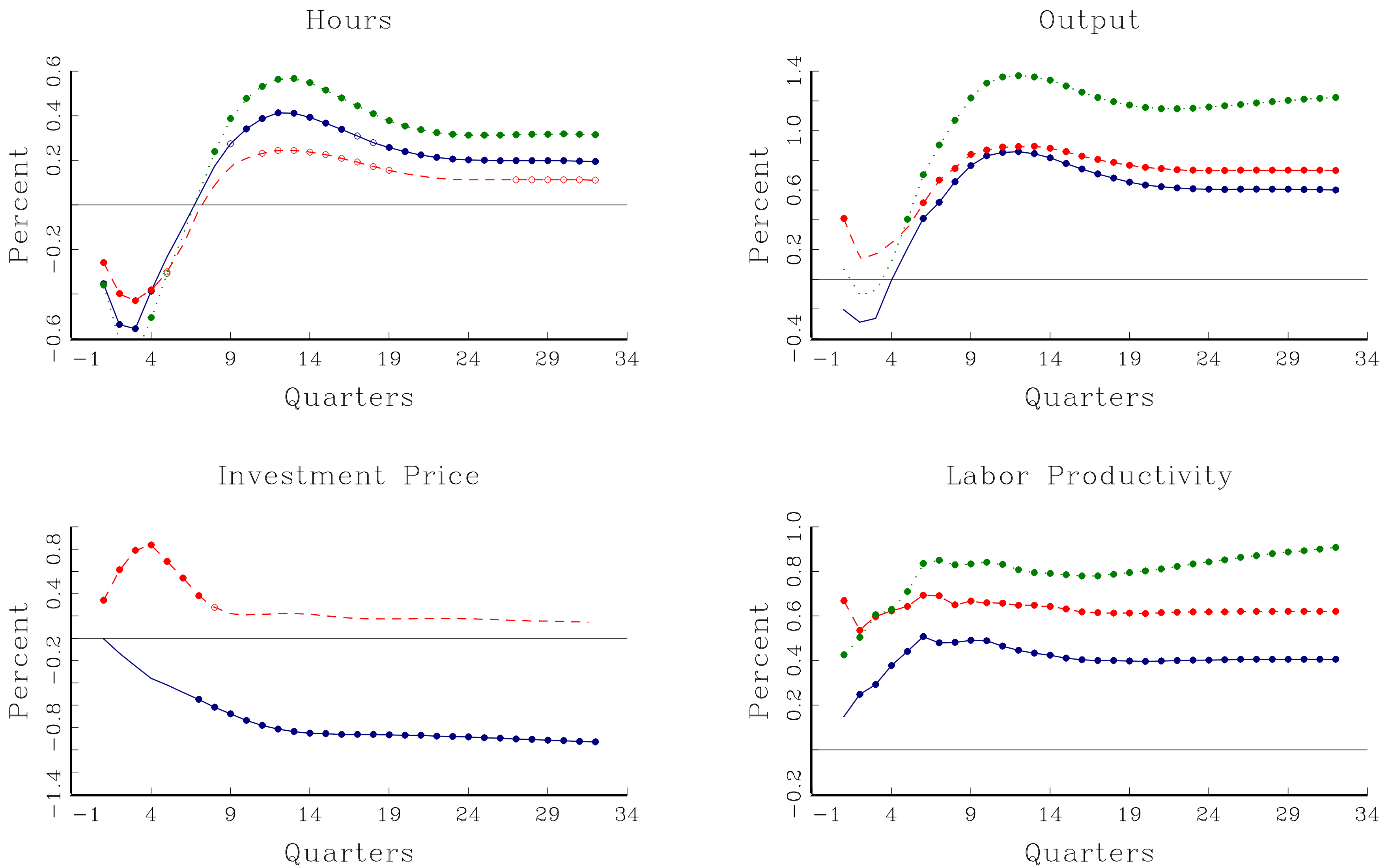
Notes: Solid lines - Respones to I-shocks in the five-variable system; Dashed lines - Respones to N-shocks in the five-variable system; Dotted lines - Responses to N-shocks in the four-variable system; Solid circles indicate the response is significant at the 5% level; Open circles indicate the response is significant at the 10% level.

Figure 7: Decomposing the contribution of technology shocks to hours in the seven-variable system



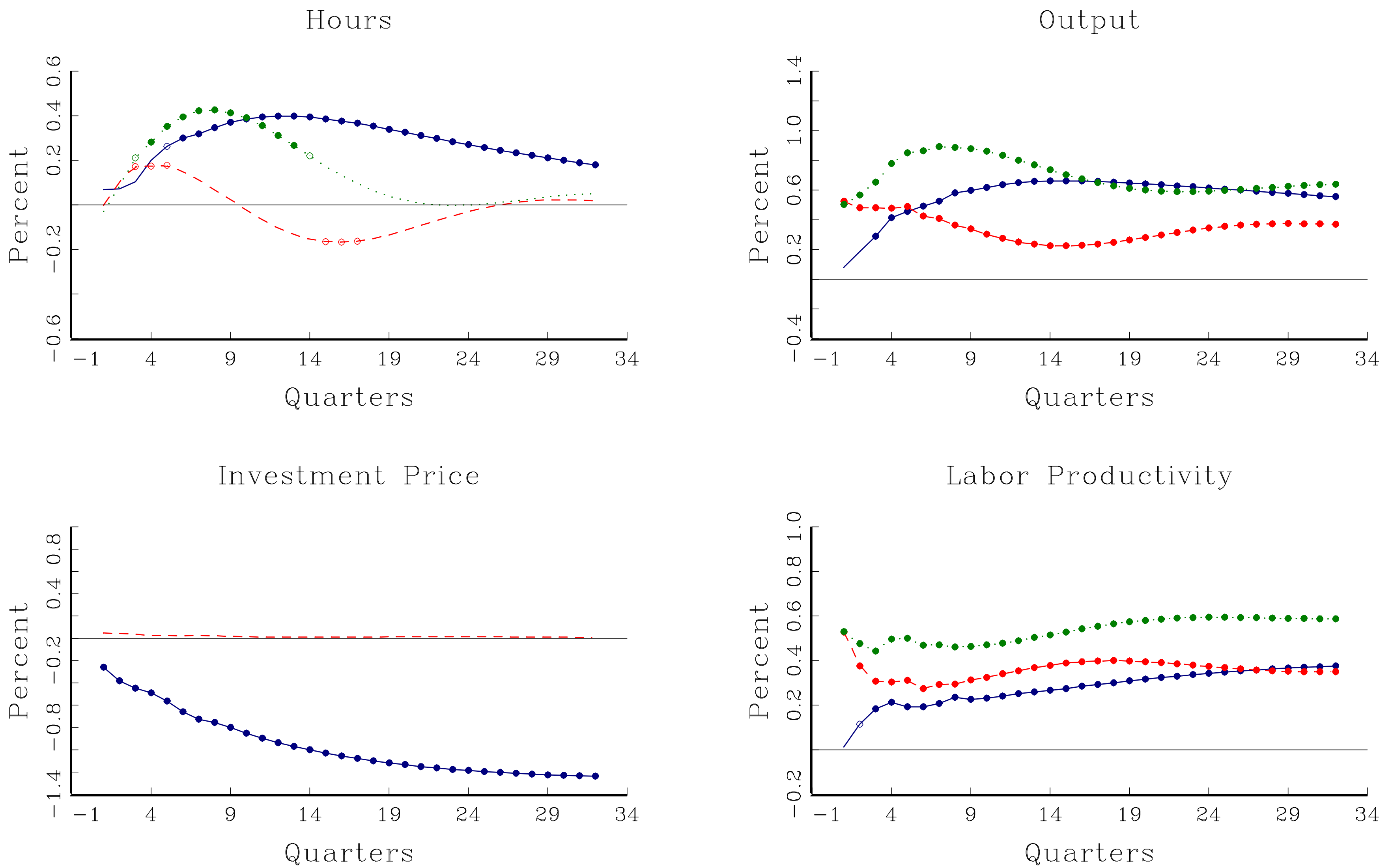
Notes: Solid lines - non-farm business hours; Dashed lines - hours due to the indicated technology shocks

Figure 8: Responses to technology shocks in the five-variable system, 1955:I-1979:II



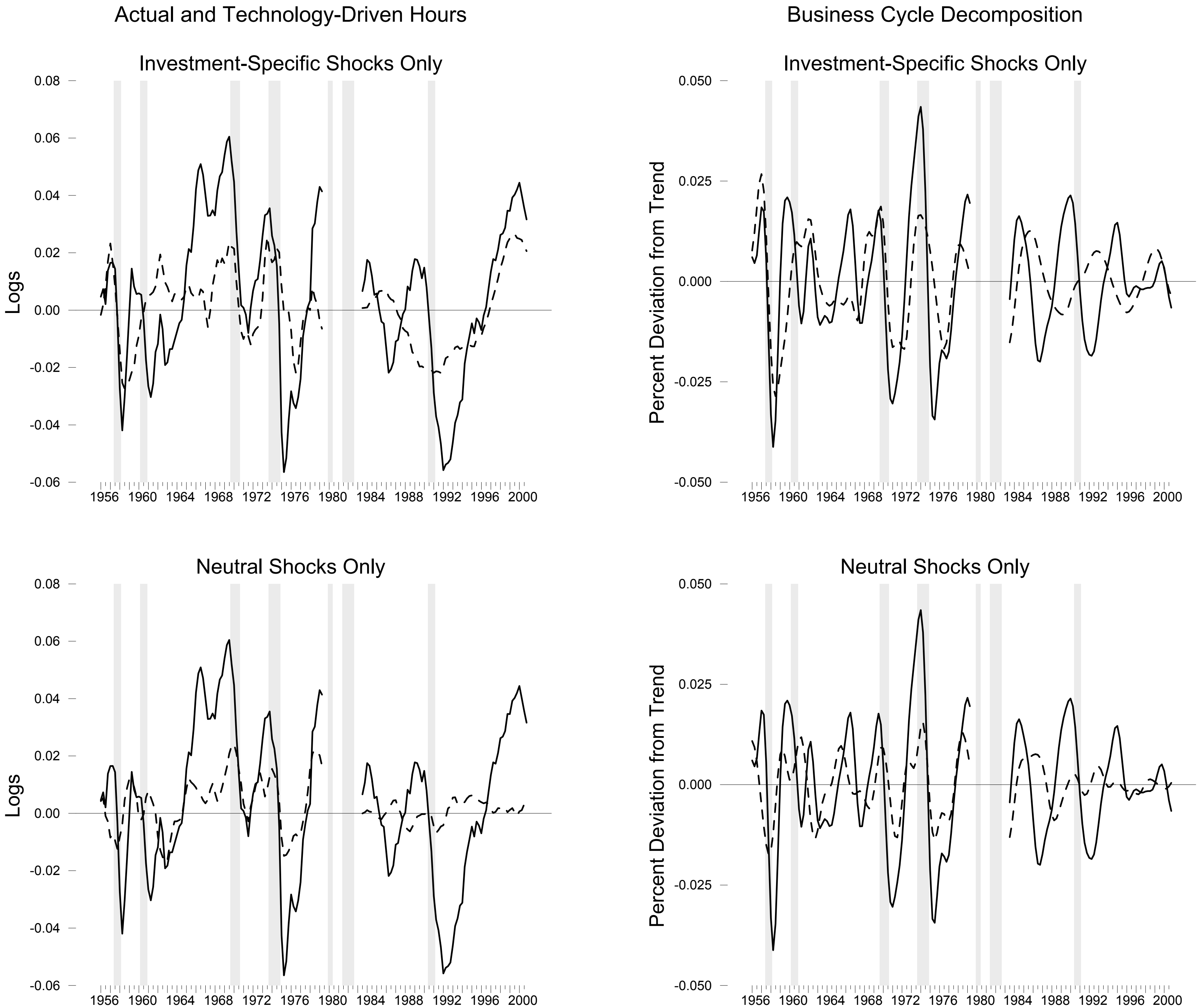
Notes: Solid lines - Respones to I-shocks in the five-variable system; Dashed lines - Respones to N-shocks in the five-variable system; Dotted lines - Responses to N-shocks in the four-variable system; Solid circles indicate the response is significant at the 5% level; Open circles indicate the response is significant at the 10% level.

Figure 9: Responses to technology shocks in the five-variable system, 1982:III-2000:IV



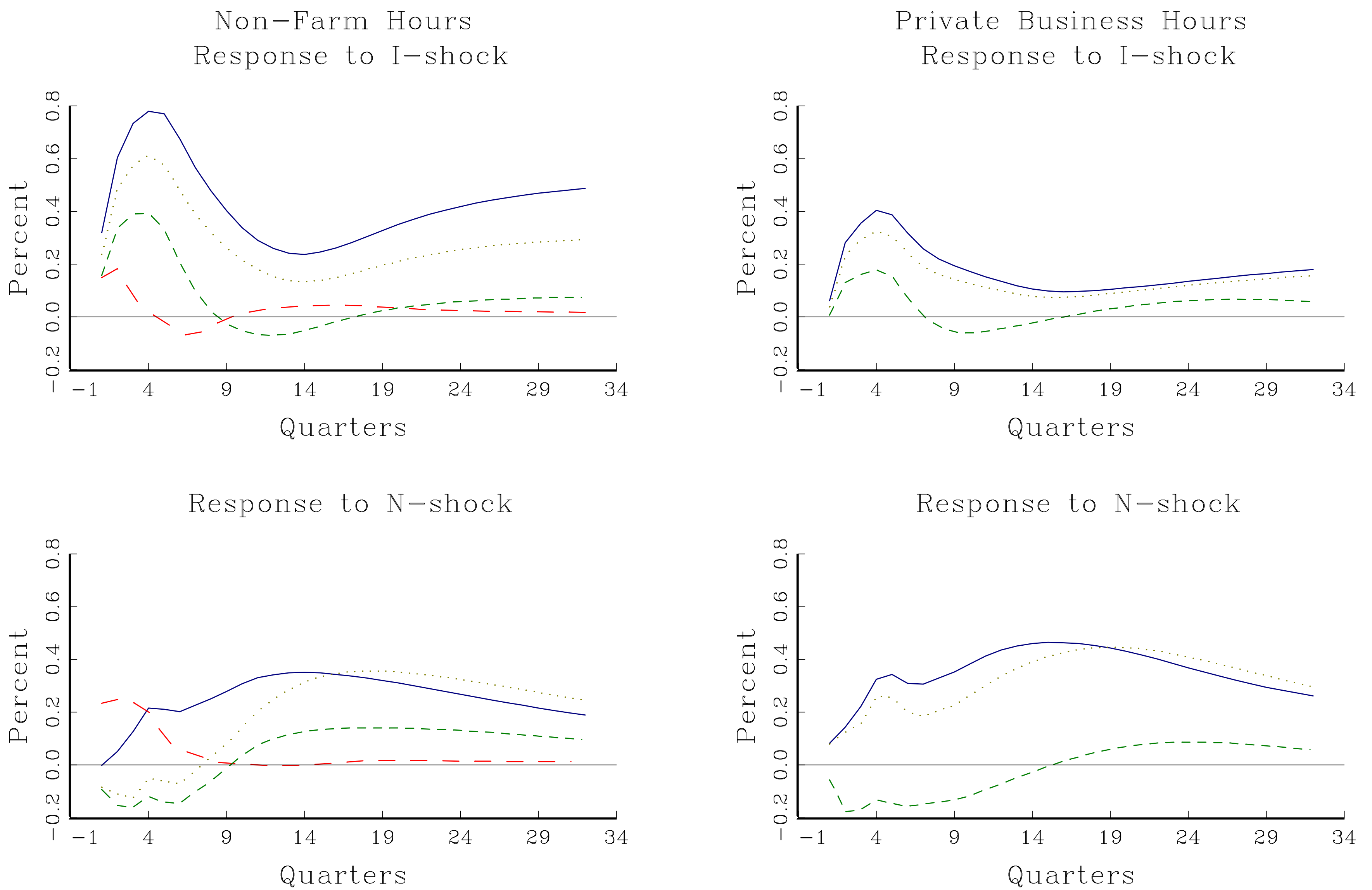
Notes: Solid lines - Respones to I-shocks in the five-variable system; Dashed lines - Respones to N-shocks in the five-variable system; Dotted lines - Responses to N-shocks in the four-variable system; Solid circles indicate the response is significant at the 5% level; Open circles indicate the response is significant at the 10% level.

Figure 10: Decomposing the contribution of technology shocks to hours in the five-variable system



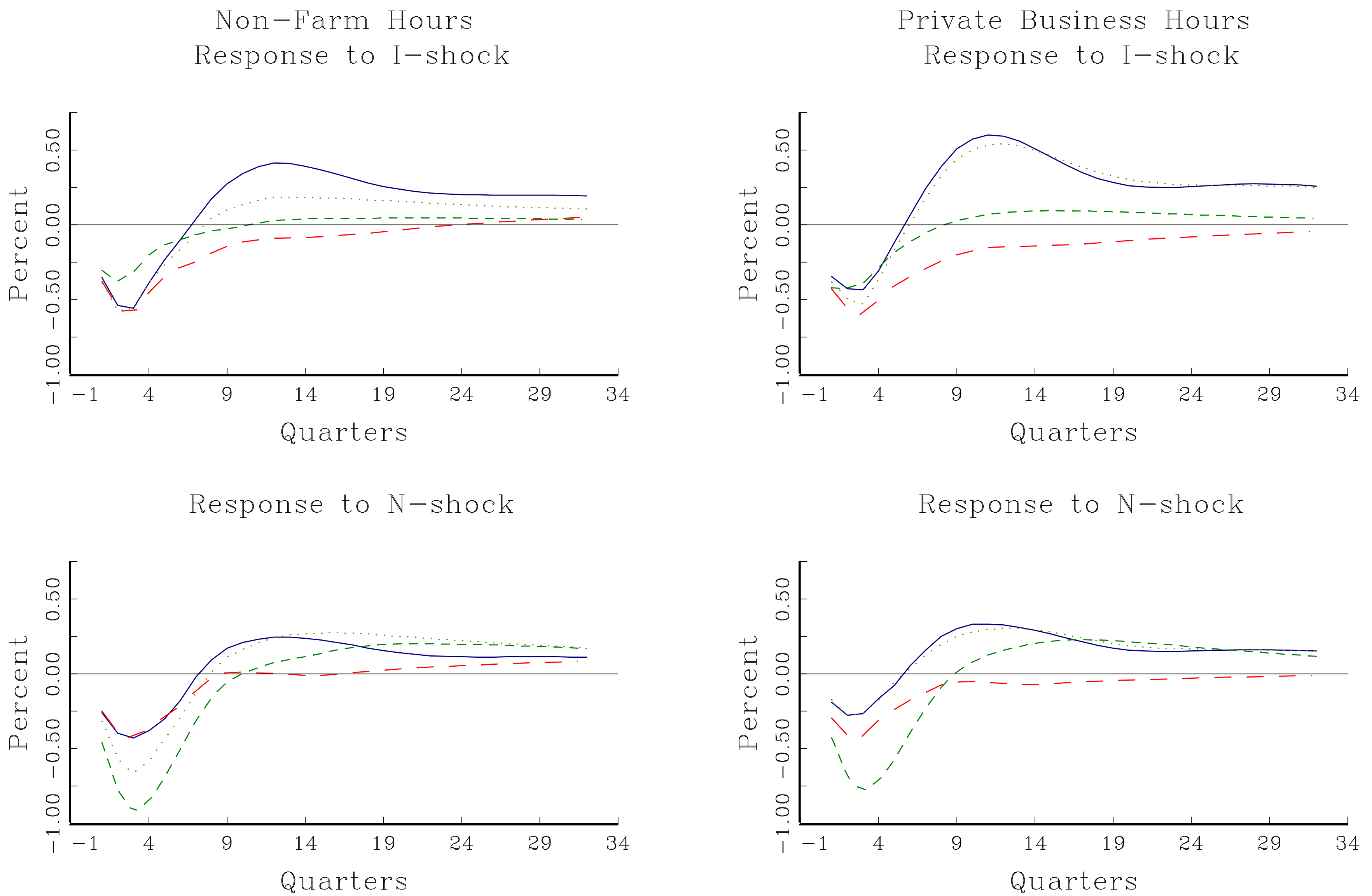
Notes: Solid lines - non-farm business hours; Dashed lines - hours due to indicated technology shocks

Figure 11. Point Estimates of Hours Response in the Seven Variable System for Different Measures of Hours, 1955:I-2000:IV



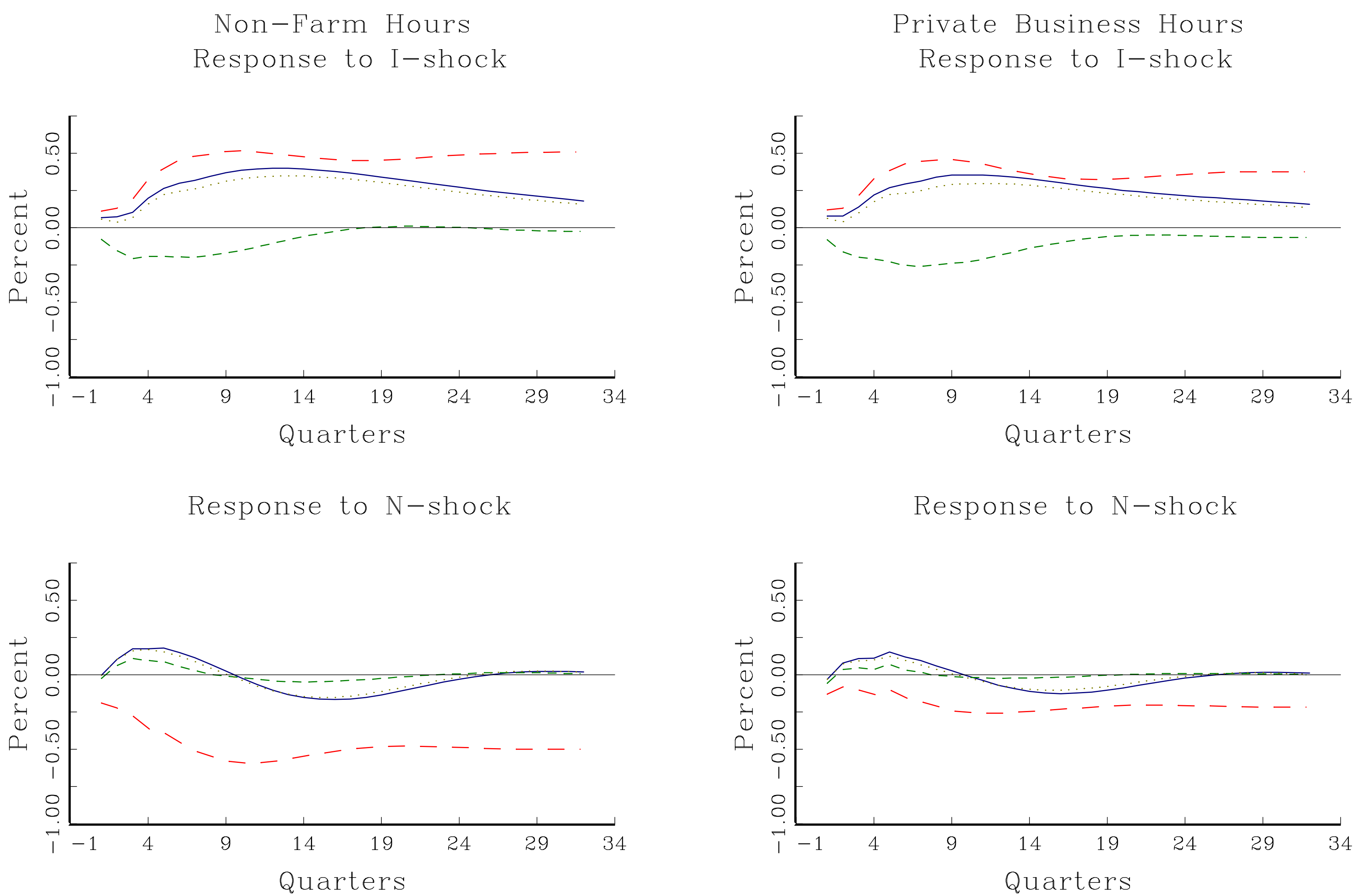
Note: Solid line - levels; Long dashed line - first differences; Short dashed line - Quadratic; Dotted line - Government Adjustment

Figure 12. Point Estimates of Hours Response in the Five Variable System for Different Measures of Hours, 1955:I-1979:II



Note: Solid line - levels; Long dashed line - first differences; Short dashed line - Quadratic; Dotted line - Government Adjustment

Figure 13. Point Estimates of Hours Response in the Five Variable System for Different Measures of Hours, 1982:III-2000:IV



Note: Solid line - levels; Long dashed line - first differences; Short dashed line - Quadratic; Dotted line - Government Adjustment