Technology Shocks and Aggregate Fluctuations*
(Preliminary and Incomplete)

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Abstract

We report estimates of the dynamic effects of a technology shock, and then use these to estimate the parameters of a dynamic general equilibrium model with money. We find: (i) a positive technology shock drives up hours worked, consumption, investment and output; (ii) the positive response of hours worked reflects that the Fed has in practice accommodated technology shocks; (iii) model parameter values and functional forms that match the response of macroeconomic variables to monetary policy shocks also work well for technology shocks; (iv) while technology shocks account for a large fraction of the lower frequency component of economic fluctuations, they account for only a small part of the business cycle component of fluctuations.

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1. Introduction

Our objective is to understand the role of technology shocks in aggregate fluctuations. To do this, we pursue an approach that has proved useful in the literature on monetary shocks. In particular, we first obtain an estimate of the dynamic macroeconomic effects of a technology shock, using reduced form methods that rely relatively little on a priori restrictions. Second, we estimate a dynamic general equilibrium model by choosing its parameters to match the estimated effects of technology shocks as closely as possible. To discipline the analysis, we also incorporate estimates of the dynamic effects of monetary policy shocks. We do this to make sure that the model which helps us understand the effects of technology shocks does not conflict in any way with models shown previously to help understand the effects of monetary policy shocks. A major result of this paper is that there is no conflict. Model parameters and functional forms shown in Christiano, Eichenbaum and Evans (2001) to fit the dynamic effects of monetary policy shocks also work for technology shocks.

We now briefly summarize our findings. To estimate the dynamic effects of technology shocks, we follow Gali (1999) and Francis and Ramey (2001) in assuming that innovations to technology shock are the only disturbance that affects the level of labor productivity in the long run. This assumption is appealing because it is a feature of standard dynamic, general equilibrium models.[1] We find that technology shocks affect macroeconomic variables very much as a student of real business cycle theory might have anticipated. A positive technology shock drives output, investment, consumption and employment up. In the case of the first two variables, the effect is permanent. There are nevertheless three surprises in our results.

[1]We have in mind models like those in Christiano (1988), King, Plosser, Stock and Watson (1991) and Christiano and Eichenbaum (1992). These models incorporate technology shocks that have a unit root, along the lines suggested by the empirical analysis in Prescott (1986). The models have the property that technology shocks are the only disturbance that has a permanent impact on labor productivity. If these real business cycle models were modified to incorporate permanent shocks to the preference for leisure (as advocated in Francis and Ramey (2001)) or to government spending, these shocks would have no long run impact on labor productivity, because this is determined by the discount rate and underlying rate of growth of technology.

Although there are many models that satisfy our identification assumption, it is not hard to think of models that do not satisfy it. For example, persistent shocks to the household discount rate will have a persistent impact on labor productivity. Similarly, any model that incorporates endogenous technical change will cause *all* shocks to have a long-run impact on labor productivity.

The previous observation is just a special case of the general fact that identifying restrictions can never be justified purely on a priori grounds. Ultimately, one builds confidence in them based on how far they take us in understanding the data.

First, the results differ sharply from what is reported in the existing literature, which argues that employment drops persistently after a positive technology shock. Our preliminary analysis of the differences suggests that the results in the existing literature primarily reflect distortions arising from omitted variable bias. To some extent, they also reflect distortions due to overdifferencing of employment data. Second, we find that although technology shocks contribute substantially to the lower frequency component of output fluctuations, they contribute relatively little to business cycle variation. Here, we hasten to emphasize that the results are based on analysis of a particular type of technology shock, one that has a permanent impact on labor productivity. As explained in the paper, in later drafts we will include other shocks to technology, and these will give us a more complete picture of the role of technology in business cycles. Until then, our provisional conclusion is that shocks to technology are not an important source of cyclical variation. In this respect, our finding corroborates the findings of the existing empirical literature on technology shocks.

Third, we find that the reason the economy responds to technology shocks the way it does has to do with monetary policy. In our reduced form estimates, monetary policy is accommodative to positive technology shocks in that money growth rises in response. The dynamic general equilibrium model that we estimate suggests that if the monetary authority did not permit money growth to be accommodative, employment would fall in response to a positive technology shock.

The following section lays out the dynamic, general equilibrium model used in the analysis. Section 3 discusses the estimation of impulse response functions. Section 4 reports results of fitting our general equilibrium model to the impulse response functions. Section 5 concludes.

2. A Dynamic, General Equilibrium Model

Following is a description of the model used in the analysis. The model builds on the one in Christiano, Eichenbaum and Evans (2001) (CEE). That model incorporates a single shock, a disturbance to monetary policy. The model used in our analysis allows for 8 shocks, including a shock to monetary policy. The discussion of this section highlights the key features of the model, including the shocks, and explains the rationale for each. The 8 shocks in the model correspond to 3 financial market shocks and 5 non-financial market shocks. The latter include three shocks to technology: a permanent and a temporary shock to the aggregate goods-producing technology, and a transient shock to the productivity of investment. In addition, we include shocks to the market power of intermediate good firms and to the market power of household suppliers of differentiated labor services. The three financial market shocks include a monetary policy shock, a shock to household money demand and a shock to firm money demand. Monetary policy is endogenous, in that the control variable of the monetary authority - the aggregate stock of money - is permitted to respond to all shocks.

The shocks have been incorporated into our quantitative model, and in a later section we describe an econometric procedure for identifying and estimating the model and shock parameters jointly. However, at this time we have only estimated the version of the model with two shocks, a shock to the technology of goods-producing firms which has long-run effects and the shock to monetary policy. A later draft will incorporate results for more shocks.

In what follows we first describe the firm sector. We then describe the household sector and equilibrium.

2.1. Firms

Final goods are produced by competitive firms who use a continuum of intermediate goods along the lines of Dixit and Stiglitz:

$$Y_t = \left[\int_0^1 Y_{jt}^{\frac{1}{\lambda_{f,t}}} dj \right]^{\lambda_{f,t}},$$

where $\lambda_{f,t}$ is a stochastic process, and $\lambda_{f,t} \in [1, \infty)$. For estimation purposes, in this draft of the paper this shock is simply fixed at its mean value, λ_f. The price of the final good is P_t and the price of the i^{th} intermediate good is P_{it}. In the usual way, competition and profit maximization lead to the following relationship between these prices:

$$P_t = \left[\int_0^1 P_{jt}^{\frac{1}{1-\lambda_{f,t}}} dj \right]^{(1-\lambda_{f,t})}. \tag{2.1}$$

The shock, λ_{ft}, shows up as a disturbance to the reduced form pricing equation of the model. Empirical analyses of inflation often find it important to include such a shock.[2]

Each intermediate good, $i \in (0,1)$ is produced by a monopolist using the following production function:

$$Y_{it} = \begin{cases} \epsilon_t \left(z_t\right)^{1-\alpha} K_{it}^{\alpha} X_{it}^{1-\alpha} - z_t^* \phi & \text{if } \left(z_t\right)^{1-\alpha} K_{it}^{\alpha} X_{it}^{1-\alpha} \geq z_t^* \phi \\ 0, & \text{otherwise} \end{cases} \tag{2.2}$$

where z_t is a persistent shock to technology, ϵ_t is a stationary shock to technology, and K_{it}, X_{it} represent capital and labor services, respectively. In this draft of the paper, we set $\epsilon_t \equiv 1$. We assume

$$x_t = \log z_t - \log z_{t-1}.$$

[2]References for this to be added here.

where

$$x_t = (1-\rho_x)x + \rho_x x_{t-1} + \varepsilon_{xt},\ x > 0. \tag{2.3}$$

We include a fixed cost in (2.2) to ensure that profits are not too big in equilibrium. We set the fixed cost parameter, ϕ, so that profits are zero along a nonstochastic steady state growth path. The fixed costs are modeled as growing with the exogenous variable, z_t^* :

$$z_t^* = z_t \Upsilon^{\left(\frac{\alpha}{1-\alpha}t\right)}, \Upsilon > 1.$$

If fixed costs were not growing, then they would eventually become irrelevant. We specify that they grow at the same rate as z_t^*, which is the rate at which equilibrium output grows. Note that the growth of z_t^* exceeds that of z_t. This is because we have another source of growth in this economy, in addition to the upward drift in z_t. In particular, we posit a trend increase in the efficiency of investment. We discuss this further below.

Intermediate good producers are competitive in the market for capital and labor services, and so they take factor prices as given. Given our specification of technology in (2.2), marginal cost is the same for each firm, and independent of the scale of production. Let s_t denote the ratio of marginal cost to the aggregate price level. Then,

$$s_t = \left(\frac{1}{1-\alpha}\right)^{1-\alpha} \left(\frac{1}{\alpha}\right)^{\alpha} \left(\frac{R_t^k}{P_t}\right)^{\alpha} \left(\frac{W_t}{P_t} R_t^f\right)^{1-\alpha},$$

where R_t^k denotes the rental rate of capital and W_t is the wage rate, both denominated in currency units. The gross nominal rate of interest, R_t^f, appears here because intermediate good firms are assumed to have to borrow a fraction, ν_t, of their wage bill at the beginning of the period, and repay it at the end, when sales receipts come due. The gross nominal rate of interest at which they borrow is R_t, so that

$$R_t^f = \nu_t R_t + 1 - \nu_t.$$

In a later draft, ν_t will be treated as a stochastic process. For now, we suppose that $\nu_t \equiv 1$.

Intermediate good firms face price frictions using a modified version of the model in Calvo (1983). In particular, each period a randomly selection fraction of firms, $1-\xi_p$, is permitted to reoptimize its price. The i^{th} firm among the ξ_p firms that do not reoptimize sets its price in the following way:

$$P_{it} = \pi_{t-1} P_{i,t-1},$$

where $\pi_t = P_t / P_{t-1}$ denotes the aggregate rate of inflation. Each intermediate good firm must satisfy its demand curve in each period. Optimizing firms discount future cash flows using the household's discount rate, $\beta \in (0,1)$.[3] This pricing behavior by firms, together with (2.1), leads to the following representation of inflation:

$$\hat{\pi}_t = \frac{1}{1+\beta}\hat{\pi}_{t-1} + \frac{\beta}{1+\beta}E_t\hat{\pi}_{t+1} + \frac{(1-\beta\xi_p)(1-\xi_p)}{(1+\beta)\,\xi_p}E_t\left[\hat{s}_t + \hat{\lambda}_{f,t}\right],$$

where a '^' over a variable indicates percent deviation from steady state.[4]

2.2. Households

The j^{th} household discounts future consumption, C_t, labor, $h_{j,t}$, and real balances, Q_t/P_t, using the following preferences:

$$E_t^j \sum_{l=0}^{\infty} \beta^l \left[u(C_{t+l} - bC_{t+l-1}) - \frac{\psi_{L,t}}{2}\left(h_{j,t}\right)^2 + \psi_{q,t}\frac{\left(\frac{Q_{t+l}}{z^*_{t+l}P_{t+l}}\right)^{1-\sigma_q}}{1-\sigma_q}\right]$$

When $b > 0$, household preferences for consumption are characterized by habit persistence. This specification of preferences is standard in the monetary economics literature because it helps account for the hump-shaped response of consumption to monetary policy shocks. In addition, this specification has proved useful for understanding features of asset prices (see Boldrin, Christiano and Fisher (2001).) The terms, $\psi_{L,t}$ and $\psi_{q,t}$, represent stochastic shocks to preferences for leisure and real balances, respectively. In this draft of the paper, these variables are simply held constant.[5]

The j^{th} household is the only supplier of a differentiated labor service, h_{jt}. It sets its wage rate, W_{jt}, following a modified version of the setup in Erceg, Henderson, Levin (2000). This in turn follows the spirit of the price setting frictions in Calvo (1983). In each period, $1-\xi_w$ households are randomly selected to reoptimize their wage. The j^{th} household among ξ_w who cannot reoptimize, set their wage according to

$$W_{jt} = \pi_{t-1}x_t W_{jt-1}.$$

[3] They actually do so using the Arrow-Debreu date and state-contingent prices. In equilibrium, these involve not just β, the household's discount factor, but also the marginal utility of consumption. However, with our linearization procedure (we use a standard procedure) the marginal utility of consumption drops out.

[4] In the case of $\hat{\lambda}_{f,t}$, this will be modeled as a zero mean, univariate time series process.

[5] From the point of interpreting $\psi_{L,t}$, it is interesting to note that this shock is observationally equivalent to a shock λ_w, a variable discussed below which measures the degree of labor market power that the household has.

Thus, non-optimizing households index their wage rate to the aggregate inflation rate, as do non-optimizing firms. In addition, non-optimizing households also add a technology growth factor to their wage. Households are required to be on their demand curve in each period. Demand for household labor derives from a competitive, representative 'labor contractor' who takes $h_{j,t}$, $j \in (0,1)$, as input and produces aggregate, homogeneous labor services using the following production function:

$$X_t = \left[\int_0^1 (h_{j,t})^{\frac{1}{\lambda_w}} dj\right]^{\lambda_w}, \; 1 \leq \lambda_w < \infty.$$

The labor contractor takes the price of labor services, W_t, as given, as well as the price of the j^{th} differentiated labor input.

The term, $\psi_{L,t}$, in the utility function is a disturbance to the preference for leisure. In the linearized solution to the model, λ_w and $\psi_{L,t}$ appear symmetrically, so we are free to interpret $\psi_{L,t}$ as a shift in the market power of workers. Various authors, including Shapiro and Watson (1988), Hall (1991), and Francis and Ramey (2001), have argued for the importance of these shocks as a source of business cycle fluctuations.

Note that we do not index C_t and Q_t in the utility function by j. In principle, different households would make different consumption and portfolio decisions because they differ in their labor market experiences. We rule out this sort of heterogeneity by the assumption that households have access to the appropriate insurance contracts.

Households own the physical stock of capital, $\bar{K}_t$. They make the investment decisions, I_t, which impact on the stock via the following capital accumulation technology:

$$\bar{K}_{t+1} = (1-\delta)\bar{K}_t + \mu_{\Upsilon,t}\Upsilon^t \left[1 - S(I_t/I_{t-1})\right] I_t. \tag{2.4}$$

The term in square brackets reflects the presence of costs of adjusting the flow of investment. We suppose that S and its derivative are zero along a steady state growth path for the economy. The second derivative of this function in steady state, $S'' > 0$, is a parameter that we estimate. We place adjustment costs on the change of investment, rather than, say, the level, to enable the model to account for the hump-shaped response of investment to a monetary policy shock.

The terms multiplying the square brackets in (2.4) represent an exogenous process governing the evolution of the efficiency of investment. There is a positive trend in this term, since $\Upsilon > 1$. This term gives rise to a trend fall in the relative price of capital goods, $P_{k',t}$, in our model economy. It captures the trend increase in the efficiency of investment that Greenwood, Hercowitz and Krusell (1998) argue is a key engine of growth for the US economy. The other term, $\mu_{\Upsilon,t}$, is a stationary stochastic disturbance to the efficiency of investment. Greenwood, Hercowitz and Krusell (1998a) argue that this is an important source of business cycle fluctuations in the US. In this draft of the paper, we set $\mu_{\Upsilon,t} \equiv 1$. In a later draft, when we estimate $\mu_{\Upsilon,t}$, we will be able to evaluate the Greenwood, Hercowitz and Krusell (1998a) claim.

Households control the amount of capital services supplied to the capital services market by choosing the utilization rate of capital. In particular, capital services are determined according to:

$$K_t = u_t \bar{K}_t.$$

To ensure that u_t is finite, we suppose that the household faces convex costs, in terms of final goods, of increasing utilization, in the form:

$$a(u_t)\Upsilon^{-t}\bar{K}_t.$$

We suppose that $a = 0$ along a steady state growth path (when $u_t = 1$) and we set a' in steady state to the scaled, real rental rate of capital. A free parameter for estimation is $a''/a' > 0$, where a'' is the second derivative of a, evaluated at $u_t = 1$. Note that for a given rate of utilization, u_t, and stock of capital, $\bar{K}_t$, the cost of utilization falls over time. This is to ensure that the model has a balanced growth steady state, one in which hours worked, capital utilization and various 'great ratios' are constant.[6] If the term were not present, the fact that the growth rate of capital is relatively rapid would imply that utilization costs would grow too fast in steady state to be consistent with $u_t = 1$.

The presence of variable capital utilization in the model, by causing the supply of capital services to be elastic, helps damp the response of marginal costs to a monetary policy shock. This in turn is key for the model's ability to account for the inertial response of inflation to a monetary policy shock. The assumption that utilization costs are denominated in goods helps assure that capital utilization rises after a positive monetary shock. In several computational experiments in which utilization costs take the form of increased depreciation of physical capital, we have found that capital utilization has a tendency to drop after a positive monetary policy shock. This is because a positive monetary shock leads to a rise in physical investment which, via the adjustment costs, leads to a rise in the price of physical capital. With capital more expensive, households find it desirable to reduce their utilization of capital.

The household has a portfolio decision. At the beginning of the period, it is in possession of the economy-wide stock of high-powered money, M_t. It splits this between deposits with a financial intermediary and Q_t. The deposits at the financial intermediary are combined with a money injection from the central bank, and loaned on to firms who need the funds

[6]By the great ratios, we mean the ratio of the consumption good value of capital to output and the ratio of consumption to output.

to finance their wage bill. The interest received by the financial intermediary on its loans is transferred to households at the end of the period. Households are willing forego interest earnings to hold Q_t, because Q_t generates services that are captured in the last term in square brackets in the utility function. The exogenous shifter, z_t^*, in the utility function guarantees that, in a steady state growth path, the ratio of Q_t/P_t to output is constant.

2.3. Monetary Authority

We adopt the following specification of monetary policy:

$$\hat{\mu}_t = \hat{\mu} + \hat{\mu}_{p,t} + \hat{\mu}_{x,t}, \tag{2.5}$$

where $\hat{\mu}_t$ represents the growth rate of high powered money, M_t. We model $\hat{\mu}_{p,t}$ and $\hat{\mu}_{x,t}$ as follows:

$$\begin{aligned} \hat{\mu}_{p,t} &= \rho_{\mu_p}\hat{\mu}_{p,t-1} + \varepsilon_{\mu_p,t} \\ \hat{\mu}_{x,t} &= \rho_{\mu_x}\hat{\mu}_{x,t-1} + c_{\mu_x}\varepsilon_{x,t} \end{aligned} \tag{2.6}$$

Here, $\varepsilon_{\mu_p,t}$ represents a shock to monetary policy and we suppose that the response of money growth to this is characterized as a scalar first order autoregression. The term, $\hat{\mu}_{x,t}$, captures the response of monetary policy to an innovation in technology, $\varepsilon_{x,t}$. The contemporaneous response is governed by the parameter, c_{μ_x}. The dynamic response of $\hat{\mu}_{x,t}$ to $\varepsilon_{x,t}$ is characterized by a first order autoregression. Initially, we worked with more elaborate parameterizations of $\hat{\mu}_{p,t}$ and $\hat{\mu}_{x,t}$. However, we found that the simple representations in (2.6) are adequate in practice.

In the discussion above, we have described 6 additional shocks: a shock to household money demand, $\psi_{q,t}$, a shock to firm money demand, ν_t, a shock to household preferences for leisure (or, equivalently, to their degree of labor market power), $\psi_{L,t}$, a stationary shock to technology, ϵ_t, an investment-specific technology shock, $\mu_{\Upsilon,t}$, and a shock to intermediate good firm market power, λ_{ft}. For now, these shocks are held constant. When they are non-trivial stochastic processes, we will add six additional terms to the representation of monetary policy, (2.5), one corresponding to the monetary policy response to each shock.

2.4. Timing, Market Clearing and Equilibrium

We adopt the following timing specification in the model. At the beginning of the period, the non-financial market shocks are realized. Then, prices and wages are set and households make their consumption, investment and capital utilization decisions. After this, the financial market shocks are realized. Then, households make their portfolio decision, goods and labor markets meet and clear, and production investment and consumption occur.

Clearing in the goods market requires:

$$C_t + I_t \leq Y_t - a(u_t)\Upsilon^{-t}\bar{K}_t,$$

where Y_t is the output of final goods. The measure of final goods and services that we compare with aggregate output in the data is $C_t + I_t$. Clearing in the money market requires:

$$W_t X_t = M_t - Q_t + (1 + \hat{\mu}_t)M_t.$$

The demand for funds appears on the left, and the supply appears on the right.

We adopt a standard sequence-of-markets equilibrium concept. The equilibrium prices and quantities in the model can be represented as follows:

$$\begin{aligned} C_t &= c_t z_t^* \\ I_t &= i_t z_t^* \\ Y_t &= y_t z_t^* \\ \bar{K}_{t+1} &= \bar{k}_{t+1} z_t^* \Upsilon^t \\ R_t^k &= P_t \Upsilon^{-t} r_t^k \\ P_{k',t} &= \Upsilon^{-t} p_{k',t} \\ W_t &= P_t z_t^* w_t. \end{aligned}$$

Here, lower case variables to the right of the equality are covariance stationary and converge to constant steady state values when all shocks are held at their unconditional mean values. Also, $P_{k',t}$ is the price of $\bar{K}_{t+1}$ at time t, in consumption goods units. According to these expressions, consumption, investment, output and the real wage grow at the rate of growth of z_t^*. The value, in consumption units, of the physical stock of capital also grows at the rate of growth of z_t^*. However, its relative price falls over time and the growth rate of the physical quantity of capital is greater than the growth rate of z_t^*. These balanced growth properties of our model are just the properties of Solow's model of investment specific technical change, recently emphasized by Greenwood, Hercowitz and Krusell (1998). An interesting feature of these properties is the logarithm of the growing variables are a linear combination of a unit root process, z_t, and a deterministic time trend, $\log(\Upsilon)t$. In practice, the literature emphasizes the possibility of one type of process, or the other, but not both.

For numerical analysis, we approximate the model's solution by linearizing the first order conditions and identities that characterize equilibrium about the non-stochastic steady state values of the scaled variables. We apply standard solution methods to the resulting linear system (see Christiano (2002).)

3. Estimation of Impulse Response Functions

We first briefly describe the data. We then describe how we go about estimating impulse responses to shocks using Vector Autoregressions. We report findings for the dynamic effects of monetary policy shocks and for a permanent shock to technology. The dynamic effects to a monetary policy shock are similar to what has been reported before in Christiano, Eichenbaum and Evans (1999, 2001). This in itself is a notable finding, because of its implications for robustness. Although the basic recursiveness assumption on monetary policy is used in all these settings, other details about the estimation vary substantially. These include the list of variables used in the analysis, the estimation period and whether the data are assumed to be trend stationary or difference stationary. Through all these applications, the basic qualitative nature of the results is always the same.

Turning to the analysis of the consequence of the permanent shock to technology, our results are in some respects surprising. In particular, we find that the response to a technology shock corresponds roughly to what a student of real business cycles would expect: hours worked, investment, consumption and output all increase. This finding is surprising because it conflicts with a recent literature which argues that hours worked actually fall after a positive shock to technology. We devote some space to reconciling our results with those in this literature. Our preliminary results suggest the possibility that the findings of this literature are consistent with the hypothesis that they are an artifact of over differencing the data. Whether this is the most plausible hypothesis is something that we are currently studying.

3.1. Data

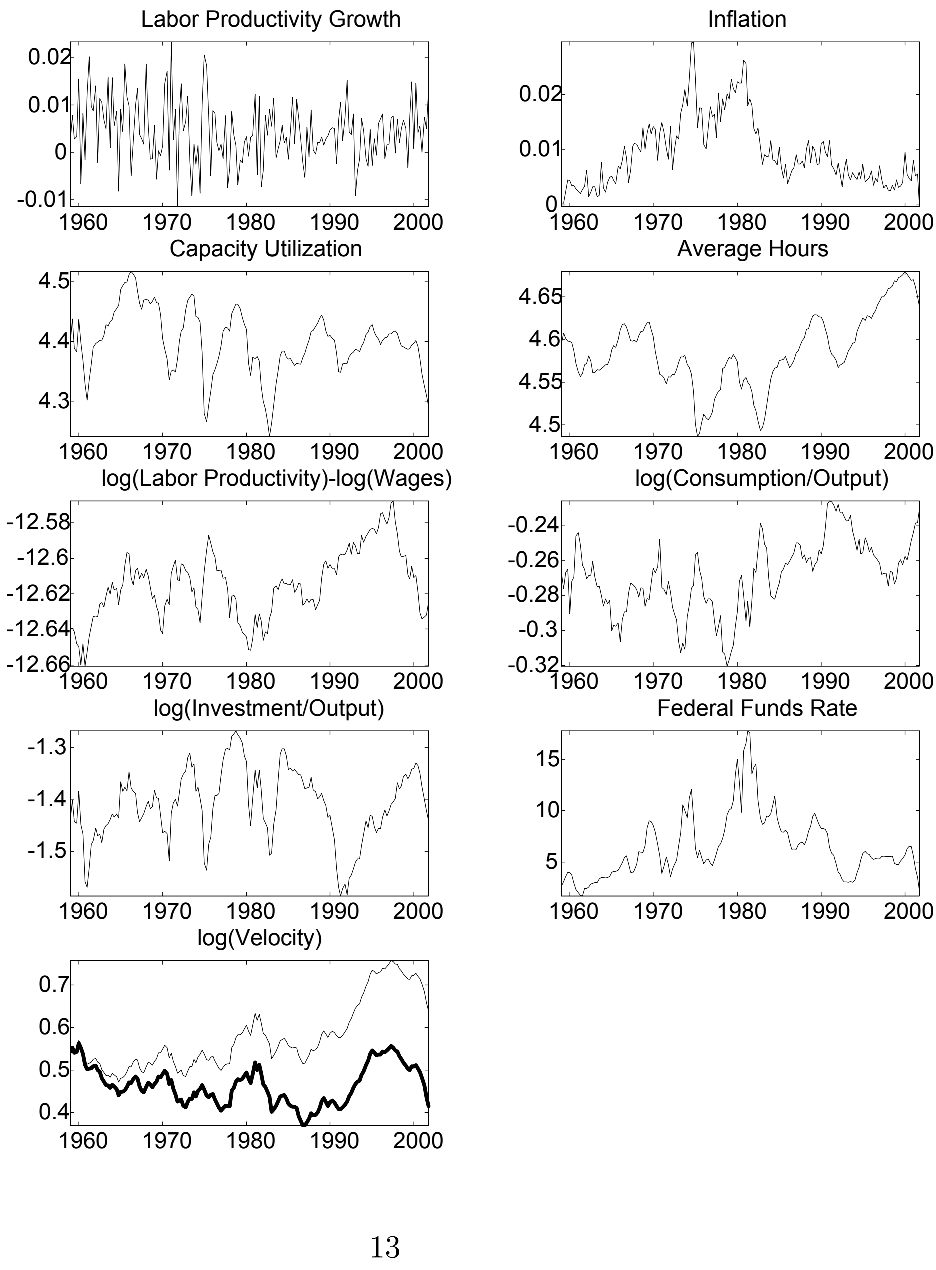
The data used in the analysis were taken from the DRI Basic Economics Database.[7] In our analysis, we require that productivity growth, the interest rate, inflation, the log consumption to output ratio, log(c/y), the log investment to output ratio, log(i/y), log capacity utilization, log per capita hours worked, the log of the productivity to real wage ratio (log(y/h)-log(w)) and the log of $M2$ velocity all be stationary. These variables are graphed in Figure 1. Thin lines indicate the raw data. For the most part, the data appear consistent with our stationarity assumption. One exception is velocity which rises very sharply in the 1990s. We detrended these data prior to analysis using a linear trend. The detrended data are indicated by the thick line. The other data were used without further transformation. The notion that the data (including detrended velocity) are covariance stationary receives support from the

[7] The data were taken from http://economics.dri-wefa.com/webstract/index.htm. Nominal gross output is measured by GDP, real gross output is measured by $GDPQ$ (real, chain-weighted output). Nominal investment is GCD (household consumption of durables) plus GPI (gross private domestic investment). Nominal consumption is measured by GCN (nondurables) plus GCS (services) plus GGE (government expenditures), money is measured by $FM2$. These variables were converted into per capita terms by $P16$, a measure of the US population over age 16. A measure of the aggregate price index was obtained from the ratio of nominal to real output, $GDP/GDPQ$. Capacity utilitzation is measured by IPXMCA the manufacturing industry's capacity index (there is a measure for total industry, IPX, but it only starts in 1967). The interest rate is measured by the federal funds rate, $FYFF$. Hours worked is measured by LBMNU (Nonfarm business hours). Hours were converted to per capita terms using our popualtion measure. Nominal wages are measured by LBCPU, (nominal hourly non-farm business compensation). This was converted to real terms by dividing by the aggregate price index.

estimated parameters of our VAR, which satisfy stationarity.

Figure 1

Data Used In VAR



3.2. Impulse Response Functions: How We Compute Them

We adopt standard strategies for identifying monetary policy and technology shocks. To identify monetary policy shocks, we adopt the recursive method pursued in CEE. To identify innovations to technology, we adopt the strategy in Gali (2001), Gali, Lopez-Salido, and Valles (2002) and Francis and Ramey (2001). In particular, we suppose - as is true in our model - that innovations to technology are the only shock that affects the level of labor productivity in the long run.[8] To identify the remaining six shocks, we developed a method of identification which we call 'model-based'. We use the restrictions implied by the model itself to do identification, using a method that is inspired by the strategy pursued recently by Uhlig (2001). Our approach differs from Uhlig's in that he imposes a priori sign and shape restrictions, while we impose the restrictions of the model.

We now discuss the calculations of the impulse response functions using the data just described. Consider the following *reduced form* vector autoregression:

$$\begin{aligned} Y_t &= \alpha + B(L)Y_{t-1} + u_t, \\ Eu_t u_t' &= V \end{aligned} \tag{3.1}$$

The 'fundamental' economic shocks, e_t, are related to u_t by the following relation:

$$u_t = Ce_t,\ Ee_te_t' = I.$$

To obtain the dynamic response function to, say, the i^{th} fundamental shock, e_{it}, we need $B(L)$ and the i^{th} column of C, C_i, and we simulate:

$$Y_t = B(L)Y_{t-1} + C_ie_{it}. \tag{3.2}$$

This section discusses how we compute $B(L)$ and C_i for the shocks we wish to identify.

[8] It is of course easy to imagine models in which *all* shocks have a permanent impact on productivity. For example, an endogenous growth model in which shocks lead to a transitory change in the rate of growth of technology has such a property. Any set of identification assumptions can be challenged on a priori grounds, and ours are no exception. Ultimately, a defense of any particular set of identification assumptions is determined by how far one can go with them in explaining empirical observations. Considerably more experience is needed before we can say with confidence what sort of identification assumptions are useful for understanding business cycle observations. This paper is part of a broader research program involving many other researchers that attempts to build the necessary experience.

In the analysis, Y_t is defined as follows:

$$\underbrace{Y_t}_{9\times 1} = \begin{pmatrix} \Delta\ln(GDP_t/\text{Hours}_t) \\ \Delta\ln(GDP\ \text{deflator}_t) \\ \text{capacity utilitzation}_t \\ \ln(GDP_t/\text{Hours}_t) - \ln(W_t/P_t) \\ \ln(\text{Hours}_t) \\ \ln(C_t/GDP_t) \\ \ln(I_t/GDP_t) \\ \text{Federal Funds Rate}_t \\ \ln(GDP\ \text{deflator}_t) + \ln(GDP_t) - \ln(M2_t) \end{pmatrix}$$

$$= \begin{pmatrix} \underbrace{\Delta y_t}_{1\times 1} \\ \underbrace{Y_{1t}}_{6\times 1} \\ \underbrace{R_t}_{1\times 1} \\ \underbrace{Y_{2t}}_{1\times 1} \end{pmatrix}.$$

We partition e_t conformably with the partitioning of Y_t :

$$e_t = \begin{pmatrix} \underbrace{\varepsilon_{xt}}_{1\times 1} \\ \underbrace{e_{1t}}_{6\times 1} \\ \underbrace{\varepsilon_t}_{1\times 1} \\ \underbrace{e_{2t}}_{1\times 1} \end{pmatrix}.$$

An alternative representation of our system is given by the *structural form*:

$$A_0 Y_t = A(L) Y_{t-1} + e_t. \tag{3.3}$$

The parameters of the reduced form are related to those of the structural form by:

$$C = A_0^{-1},\ B(L) = A_0^{-1} A(L). \tag{3.4}$$

We obtain impulse responses by first estimating the parameters of the structural form, then mapping these into the reduced form, and finally simulating (3.2). We specify the VAR to have four lags, so that $A(L) = A_1 + A_2 L + A_3 L^2 + A_4 L^3$. Our data are quarterly and cover the period is 1959QI - 2001QIV (the estimation period drops the first 4 quarters, to accommodate the 4 lags).

The following two subsections consider first, identification of the monetary policy and technology shocks, and then identification of the other shocks.

3.2.1. Restrictions on Monetary Policy and Technology Shocks

We assume policy makers manipulate the monetary instruments under their control in order to ensure that the following interest rate targeting rule is satisfied:

$$R_t = f(\Omega_t) + \varepsilon_t, \tag{3.5}$$

where ε_t is the monetary policy shock. We interpret this as a kind of 'reduced form' Taylor rule. Conventional representations of the Taylor rule include a smaller set of variables than we do. Typically, these 'structural representations' of the Taylor rule include expected future inflation and the output gap. We interpret our (3.5) as a convolution of the structural representation of the Taylor rule with the (linear) functions which relate the variables in the structural Taylor rule to the variables in our VAR. By representing the Taylor rule in this way, we sidestep difficult and controversial questions, such as how it is that the monetary authorities actually compute the output gap. To ensure identification of the monetary policy shock, we assume f is linear, Ω_t contains Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-4} and the only date t variables in Ω_t are the ones above R_t in Y_t. Finally, we assume that ε_t is orthogonal with Ω_t. It is easy to verify (see, e.g., Christiano, Eichenbaum and Evans (1999)) that these identifying assumptions correspond to the following restrictions on A_0 :

$$A_0 = \begin{bmatrix} \underset{1\times1}{A_0^{1,1}} & \underset{1\times6}{A_0^{1,2}} & \underset{1\times1}{0} & \underset{1\times1}{0} \\ \underset{6\times1}{A_0^{2,1}} & \underset{6\times6}{A_0^{2,2}} & \underset{6\times1}{0} & \underset{6\times1}{0} \\ \underset{1\times1}{A_0^{3,1}} & \underset{1\times6}{A_0^{3,2}} & \underset{1\times1}{A_0^{3,3}} & \underset{1\times1}{0} \\ \underset{1\times1}{A_0^{4,1}} & \underset{1\times6}{A_0^{4,2}} & \underset{1\times1}{A_0^{4,3}} & \underset{1\times1}{A_0^{4,4}} \end{bmatrix}. \tag{3.6}$$

To understand this, consider first the second to last row of A_0. This row corresponds to the monetary policy rule, (3.5), and the zero in this row reflects that the monetary authority does not look at the last variable in Y_t. Now consider the first 7 rows. The right two columns reflect our assumption that a monetary policy shock has no contemporaneous impact on Δy_t

or Y_{1t}. The two sets of zeros reflect the two distinct channels by which this impact could occur. The second to last column of zeros reflects that the interest rate cannot enter directly into the first set of 7 equations. The second reflects that the interest rate cannot also enter indirectly, via its contemporaneous impact on the last variable.

The assumption that only the technology shock has a non-zero impact on the level of output at infinity implies that the matrix

$$A_0 - A(1), \tag{3.7}$$

has all zeros in its first row, except the 1,1 element, which could potentially be non-zero. To see this, note that the impact of the vector of shocks on the level of y_t at $t = \infty$ corresponds to the first row of $[A_0 - A(1)]^{-1}$. Thus, our long-run restriction is that only the first element in the first row may be non-zero, while the others are zero. But, this is true if, and only if, the same restriction is satisfied by (3.7).

It is useful to write out the equations explicitly, taking into account the restrictions implied by our assumptions about long-run effects, and by our assumptions about the effects of a monetary policy shock:

$$\Delta y_t = a_{\Delta y}(L)\Delta y_{t-1} + \tilde{a}_1(L)\Delta Y_{1t} + \tilde{a}_R(L)\Delta R_{t-1} + \tilde{a}_2(L)\Delta Y_{2,t-1} + \frac{\varepsilon_{xt}}{A_0^{1,1}},$$

where $\Delta = (1 - L)$, and the polynomial lag operators correspond to the relevant entries of the first row of $A_0 - A(L)L$, scaled by $A_0^{1,1}$. Note that among the right hand variables in this expression, the only one whose current value appears here is ΔY_{1t}. This fact rules out ordinary least squares as a strategy for obtaining a consistent estimate of the coefficients in this equation, because we expect ε_{xt} to be correlated with ΔY_{1t}. An instrumental variables method can be constructed based on the insight that lagged variables are correlated with ΔY_{1t}, but not with ε_{xt}. Suppose that an initial consistent estimate of the coefficients have been obtained in this way. The coefficients in the first row of the structural form can then be obtained by scaling the instrumental variables estimates up by $A_0^{1,1}$, where $A_0^{1,1}$ is estimated as the (positive) square rood of the variance of the fitted disturbances in the instrumental variables relation.

The next set of 6 equations can be written as follows:

$$A_0^{2,1}\Delta y_t + A_0^{2,2}Y_{1t} = b(L)Y_{t-1} + e_{1t} \tag{3.8}$$

The following equation is just the policy rule:

$$R_t + \frac{A_0^{3,1}}{A_0^{3,3}}\Delta y_t + \frac{A_0^{3,2}}{A_0^{3,3}}Y_{1t} = c(L)Y_{t-1} + \frac{\varepsilon_t}{A_0^{3,3}}.$$

Consistent estimates of the parameters in this expression may be obtained by ordinary least squares with R_t as the dependent variable, by our assumption that ε_t is not correlated with Δy_t and Y_{1t}. The parameters of the 8^{th} row of the structural form are obtained by scaling the estimates up by $A_0^{3,3}$, where $A_0^{3,3}$ is estimated as the positive square root of the variance of the fitted residuals. Finally, according to the last equation:

$$Y_{2t} + \frac{A_0^{4,1}}{A_0^{4,4}}\Delta y_t + \frac{A_0^{4,2}}{A_0^{4,4}}Y_{1t} + \frac{A_0^{4,2}}{A_0^{4,4}}R_t = d(L)Y_{t-1} + \frac{e_{2t}}{A_0^{4,4}}.$$

The coefficients in this relation can be estimated by ordinary least squares. This is because e_{2t} is not correlated with the other contemporaneous variables in this relation. This reflects that Y_{2t} does not enter any of the other equations. The parameter, $A_0^{4,4}$, can be estimated as the square root of the estimated variance of the disturbances in this relation. The parameters in the last row of the structural form are then estimated suitably scaling up by $A_0^{4,4}$.

The previous argument establishes that the 1^{st}, 8^{th} and last rows of A_0 are identified. The block of 6 rows in the middle are not identified. To see this, let w denote an arbitrary 6×6 orthonormal matrix, $ww' = I_6$. Suppose $\bar{A}_0$ and $\bar{A}(L)$ is some set of structural form parameters that satisfies all our restrictions. Let the orthonormal matrix, W, be defined as follows:

$$W = \begin{bmatrix} 1 & \underset{1\times 6}{0} & 0 & 0 \\ \underset{6\times 1}{0} & \underset{6\times 6}{w} & \underset{6\times 1}{0} & \underset{6\times 1}{0} \\ 0 & \underset{1\times 6}{0} & 1 & 0 \\ 0 & \underset{1\times 6}{0} & 0 & 1 \end{bmatrix}. \tag{3.9}$$

It is easy to verify that the reduced form corresponding to the parameters, $W\bar{A}_0$, $W\bar{A}(L)$ also satisfies all our restrictions, and leads to the same reduced form:

$$Y_t = \left(W\bar{A}_0\right)^{-1} W\bar{A}(L)Y_{t-1} + \left(W\bar{A}_0\right)^{-1} We_t.$$

To see this, note:

$$\begin{aligned} \left(W\bar{A}_0\right)^{-1} W\bar{A}(L) &= \bar{A}_0^{-1}W'W\bar{A}(L) = \bar{A}_0^{-1}\bar{A}(L) \\ E\left(W\bar{A}_0\right)^{-1} Wu_tu_t'W'\left[\left(W\bar{A}_0\right)^{-1}\right]' &= E\bar{A}_0^{-1}W'We_te_t'W'\left[\bar{A}_0^{-1}W'\right]' \\ &= E\bar{A}_0^{-1}W'We_te_t'W'W\left(\bar{A}_0^{-1}\right)' \\ &= \bar{A}_0^{-1}W'WW'W\left(\bar{A}_0^{-1}\right)' \\ &= \bar{A}_0^{-1}\left(\bar{A}_0^{-1}\right)'. \end{aligned}$$

Recall that impulse response functions can be computed using the matrices in $B(L)$ and the columns of A_0^{-1}. It is easy to see that the impulse responses to ε_{xt}, ε_t and e_{2t} are invariant to w. This is because:

$$\left(W\bar{A}_0\right)^{-1} = \bar{A}_0^{-1}W'.$$

It is easily verified that the first, 8th and last columns of $\bar{A}_0^{-1}W'$ coincide with those of $\bar{A}_0^{-1}$.

We conclude that there is a family of observational equivalent parameterizations of the structural form, which is consistent with our identifying assumptions on the monetary policy shock and the technology shock. We arbitrarily select an element in this family as follows. Let Q and R be orthonormal and lower triangular (with positive diagonal terms) matrices, respectively, in the QR decomposition of A_0^{22}. That is, $A_0^{22} = QR$. This decomposition is unique and guaranteed to exist given that A_0^{22} is non-singular, a property implied by our assumption that A_0 is invertible. The reasoning up to now indicates that we may, without loss of generality, select A_0 so that A_0^{22} is lower triangular with positive diagonal elements. This restriction does not restrict the reduced form in any way, nor does it restrict the set of possible impulse response functions associated with ε_{xt}, ε_t or e_{2t}.

Thus, in (3.8) A_0^{22} is lower triangular. We seek consistent estimates of the parameters of (3.8), with this restriction imposed. Ordinary least squares will not work as an estimation procedure here because of simultaneity. To see this, consider the first equation in (3.8). Suppose the left hand variable is the first element in Y_{1t}. The only current period explanatory variable is Δy_t. But, note from the first equation in the structural form that Δy_t responds to Y_{1t} and, hence, to the innovations in Y_{1t}. That is, Δy_t is correlated with the first element in e_{1t}. We can instrument for Δy_t using ε_{xt}, the (scaled) residual from the first structural equation. Clearly, this variable is correlated with Δy_t, and not with the first element in e_{1t}.

Now consider the second equation in (3.8). Think of the left hand variable as being the second variable in Y_{1t}. The current period explanatory variables in that equation are Δy_t and the first variable in Y_{1t}. Both these are correlated with the second element in e_{1t}. To see this, note that a disturbance in the second element of e_{1t} ends up in Δy_t via the first equation in the structural form, because Y_{1t} appears there. This explains why Δy_t is correlated with the second element of e_{1t}. But, the first element in Y_{1t} is also correlated with this variable because Δy_t is an 'explanatory' variable in the equation determining the first element in Y_{1t}, i.e., the first equation in (3.8). So, we need an instrument for Δy_t and the first element of Y_{1t}. For this, use ε_{xt} and the residual from the first equation in (3.8). Thus, moving down the equations in (3.8), we use as instruments ε_{xt} and the disturbances in the previous equations in (3.8).

With A_0 and $A(L)$ in hand, we are now in a position to compute the reduced form, using (3.4). In that reduced form, we find it convenient to refer to the shocks, e_{1t}, as Choleski shocks, because of the lower triangular normalization that underlies them. The dynamic response of Y_t to technology and monetary policy shocks may be computed by simulating (3.2) with $i = 1, 8$, respectively.

3.2.2. Model-Based Identification of Other Shocks

We now consider identification of other shocks in the model. The previous subsection discussed the computation of A_0 and $A(L)$ with the normalization that A_0^{22} is lower triangular and imposing our assumptions on monetary policy and technology shocks. From that discussion, we know that if W is an orthonormal matrix with structure (3.9), then WA_0 and $WA(L)$ is another parameterization of the structural form which satisfies the identification assumptions on monetary policy and technology shocks. That parameterization replaces the Choleski shocks, e_{1t}, with a linear combination, We_{1t}. The new vector of shocks, We_{1t}, has a different set of impulse response functions. The idea of model-based identification is to search over all possible such shocks, to identify the orthonormal rotation matrix, say W^*, such that the dynamic response in the VAR to W^*e_{1t} resembles the model's dynamic responses to shocks other than ε_{xt}, ε_t and e_{2t}. Our metric for making precise 'resembles' is discussed further below.

The discussion in the previous paragraph supposes that we wish to identify 6 additional structural shocks based on rotations of the 6 Choleski shocks, e_{1t}. However, in our work we plan to start by identifying a smaller set of shocks, say three. To do this, we need to identify a way to 'ignore' a subset of the shocks in e_{1t}. One way to do this is to identify the elements in the space of orthonormal rotations of e_{1t} that corresponds to the principal components of one or several of the variables in our analysis. We choose to focus on output. We call the shocks associated with this rotation, the 'principal component shocks'. Our new basis of shocks is formed by the most important of the three principal component shocks. Our method of identifying these shocks follows the approach taken in Uhlig (2002).

To explain the method, let $\tilde{w}$ denote a 6-dimensional column vector and consider the linear combination of e_{1t}, $\tilde{w}'e_{1t}$. Let a denote the 20×6 matrix containing the first 20 responses in the log level of output to the six Choleski shocks, e_{1t}. Then, $a\tilde{w}$ denotes the 20×1 column vector containing the first 20 responses of log output to the shock, $\tilde{w}'e_{1t}$. We seek a $\tilde{w}$ such that 20-quarter ahead forecast error variance in log output due to $\tilde{w}'e_{1t}$ is as large as possible, subject to $\tilde{w}'\tilde{w} = 1$. Since this forecast error variance is the sum of squares of the elements in $a\tilde{w}$, the Lagrangian representation of the problem solved by $\tilde{w}$ is:

$$\max_{\tilde{w}} \tilde{w}'a'a\tilde{w} - \lambda \left[\tilde{w}'\tilde{w}' - 1\right],$$

where λ is the multiplier on the constraint. As is well known from the principal components literature, the unique solution to this problem is the eigenvector associated with the largest eigenvalue of $a'a$. Let this eigenvector of a be denoted $\tilde{w}_1$. We now identify another column vector, $\tilde{w}$, such that the 20-quarter ahead forecast error variance in log output due to $\tilde{w}'e_{1t}$ is as large as possible, subject to $\tilde{w}'\tilde{w}_1 = 0$ and $\tilde{w}'\tilde{w} = 1$. Note that this shock is orthogonal to $\tilde{w}_1'e_{1t}$, the first principal component shock. The Lagrangian representation of the problem solved by $\tilde{w}$ is:

$$\max_{\tilde{w}} \tilde{w}'a'a\tilde{w} - \lambda\left[\tilde{w}'\tilde{w} - 1\right] - \mu\tilde{w}_1'\tilde{w},$$

where λ and μ are multipliers. It is well known that the unique solution to this problem is the eigenvector, $\tilde{w}_2$, associated with the second largest eigenvalue of $a'a$. Proceeding in this way, we obtain $\tilde{w}_3, ..., \tilde{w}_6$ as the eigenvectors associated with successively smaller eigenvalues of $a'a$. Note that by construction, the matrix W formed from $w' = [\tilde{w}_1, ..., \tilde{w}_6]$ satisfies orthonormality.

It is of interest to see what fraction of the 20-quarter ahead variance of output due to e_{1t} the principal component shocks, $\tilde{w}_i e_{1t}$, $i = 1, ..., 6$ explain. We found that the first principal component shock, $\tilde{w}_1 e_{1t}$, accounts for 66% of the variance of output at the 20 quarter horizon, the second accounts for 25% and the third accounts for 7%. The other principal component shocks taken together account for 2% or less.[9] These results suggest that not much is lost by simply focusing on orthogonal rotations of the first three principal component shocks. We are doing this now and plan to report the results of identifying three additional fundamental shocks in this way in the next draft. The three additional shocks are the other two technology shocks and the preference for leisure shock.

3.3. Impulse Response Functions: The Results for Monetary Policy and Technology

The procedure defined in the previous section allows us to determine the dynamic response to monetary policy and technology shocks independent of our dynamic equilibrium model. This is not so for the other shocks. Our model-based identification procedure is interactive with our model. The remainder of this section discusses results for policy and technology shocks.

Figure 2 displays the response of our variables to a monetary policy shock. In each case, there is a solid line in the center of a gray area. The gray area represents a 95% confidence interval, and the solid line represents the point estimates.[10] Note how all variables but the interest rate and money growth show zero response in the period of the shock. This

[9]We repeated the calculations with log output replaced by log hours worked. The results were essentially the same.

[10]The confidence intervals are constructed using standard error estimates of impulse responses obtained using bootstrap simulations.

reflects the identification assumption underlying our monetary policy shock. Note too, that the variables displayed in Figure 2 are transformations of the variables in Y_t, which are displayed in Figure 1. In all cases but inflation and the interest rate, the variables are in percent terms. Thus, the peak response of output is a little over 0.2 percent. The Federal Funds rate is in units of basis points, at an annual rate. So, the policy shock produces a 60 basis point drop in the federal funds rate. Inflation is expressed at a quarterly rate. In analyzing these results, we focus on the first 20 quarters' responses.

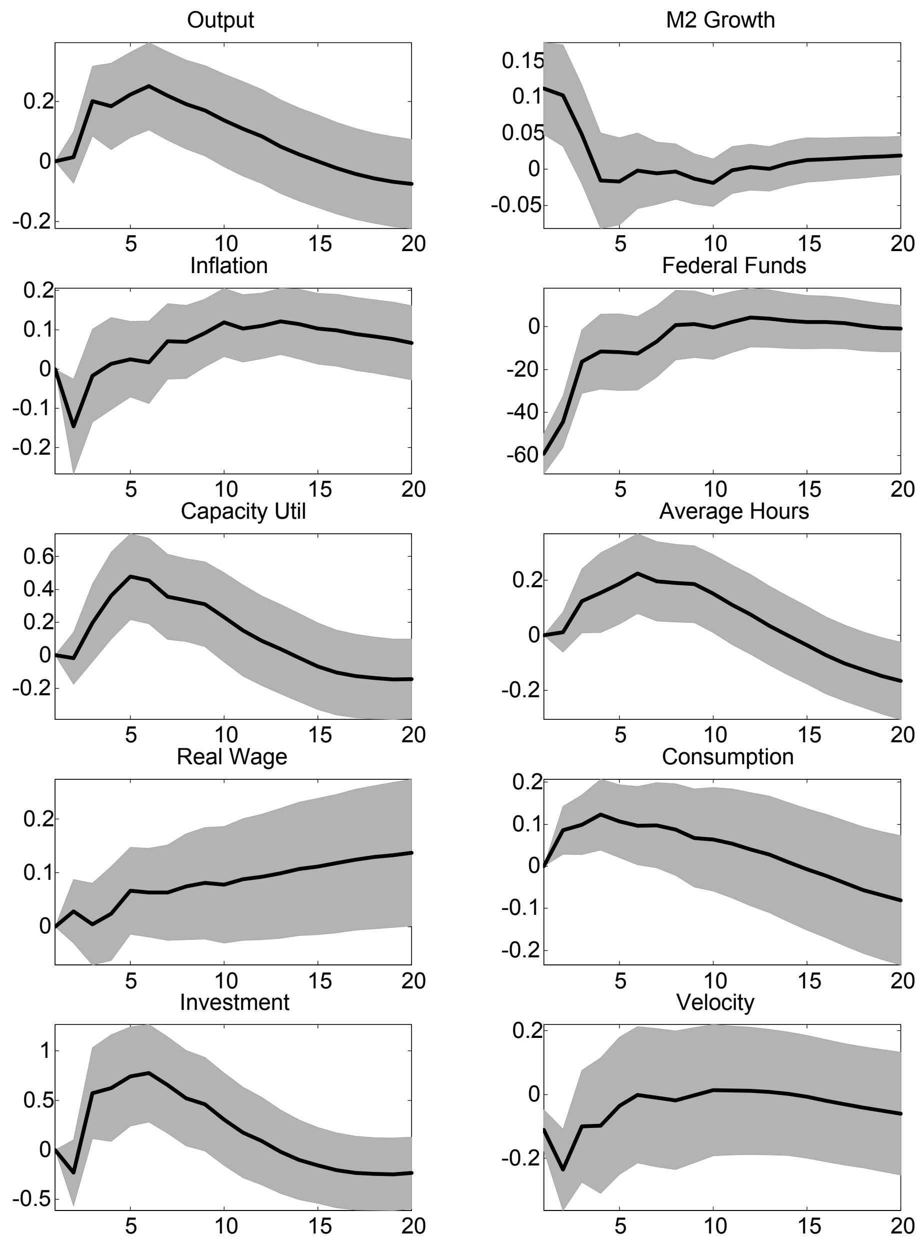
There are six features worth emphasizing here. First, however one measures the policy variable - whether by money growth or the interest rate - the policy variable has completed its movement within about one year. The other variables respond over a longer period of time. Clearly, any model that can explain these movements must exhibit a substantial amount of internal propagation. Second, inflation takes nearly 3 years to reach its peak response. This is a measure of the substantial inertia in this variable. Interestingly, the initial response of inflation to the monetary expansion is a marginally significant negative fall. In the literature, this has been referred to as the 'price puzzle', reflecting a presumption that no sensible model could reproduce it. The importance of working capital in the monetary transmission mechanism of the model, which causes the interest rate to enter marginal costs, ensures that our model can in principle account for this.[11] Third, output, consumption, investment, hours worked and capacity utilization all display hump-shaped responses, that peak after roughly one year. Fourth, there is a significant liquidity effect. That is, the results indicate that to get the interest rate down, the policy authority must increase money growth.[12] Fifth, velocity moves in the direction naive theory would predict, falling with the initial fall in the

[11] The role of the working capital channel in providing a resolution to the price puzzle has been emphasized by Barth and Ramey.

[12] In interpreting $M2$ as a policy variable, we implicitly assume that the monetary authority can achieve any degree of control over $M2$ that it wishes by suitably manipulating bank reserves.

interest rate. Finally, the real wage exhibits a strong positive response.

Figure 2: Impulse Responses to a Monetary Policy Shock

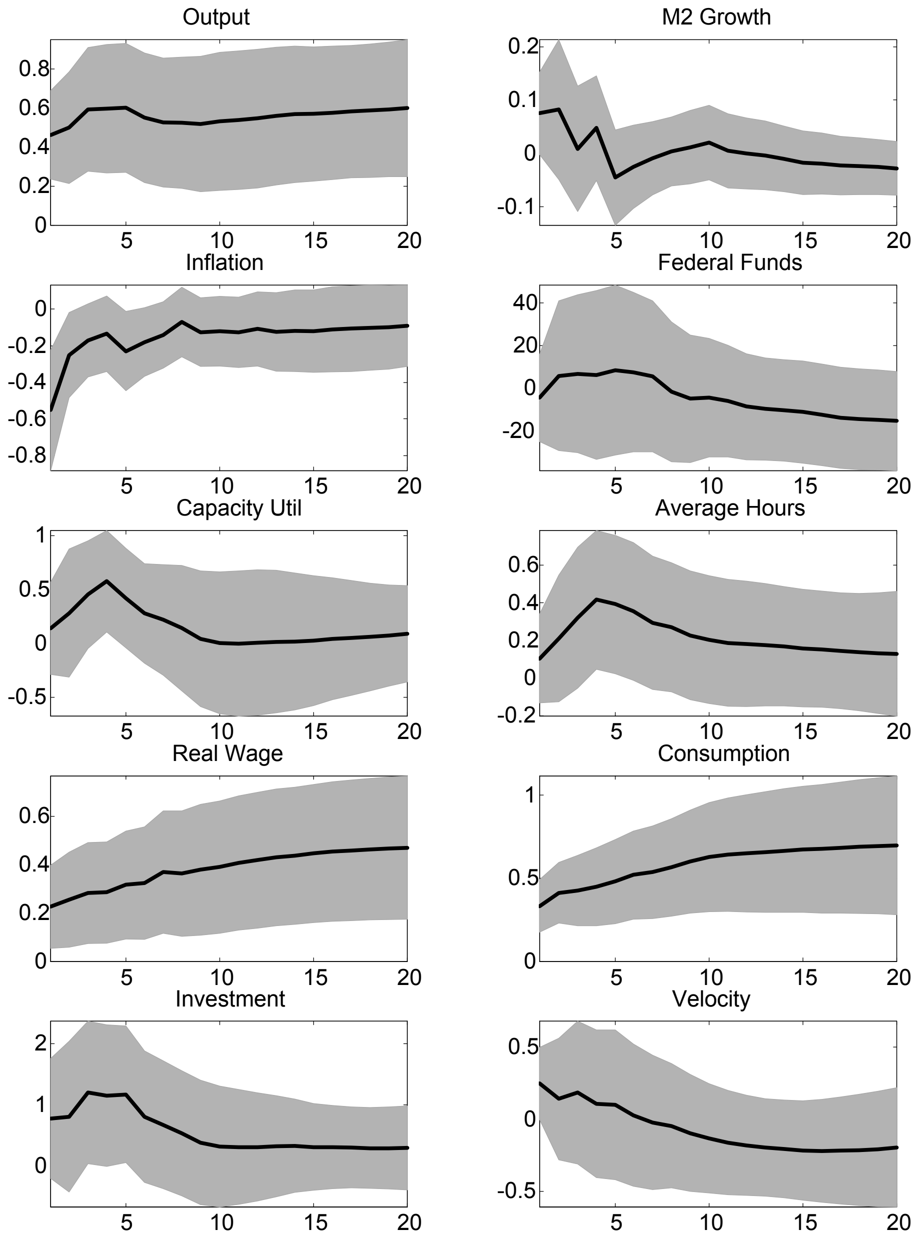


Next we discuss the response of the economy to a positive technology shock. This is displayed in Figure 3. All responses are measured in the same units as in the previous figures. By construction, the impact of the technology shock on output, labor productivity, consumption, investment and the real wage can be permanent. Because the roots of our estimated VAR are stable, the impact of technology on the variables whose levels appear in Y_t must be temporary. These variables include capacity utilization, hours worked and inflation.

According to the results in Figure 3, the effect of a one-standard deviation positive technology shock is to increase output by about one-half of one percent. The initial reaction of capacity utilization and hours worked to a positive technology shock is (weakly) positive. Overall, our point estimates of the response of variables to a technology shock corresponds qualitatively to what a student of real business cycle models might expect. This contrasts with recent papers in the literature, which report point estimates which suggest that the labor input falls for a prolonged period of time in the wake of a positive technology shock.

The next subsection discusses the relationship between our work and this literature.

Figure 3: Impulse Responses to an Innovation in Technology



We now discuss the decomposition of variance of our two variables. The percent of forecast error variance due to monetary policy shocks, at horizons 1, 4, 8, 12 and 30 quarters, is reported in Table 1. The final column, labeled HP, reports the percent of the variance in business cycle frequencies due to monetary policy shocks. We compute this by first simulating the VAR driven only by the estimated monetary policy shocks, and computing the variance of the simulated data after applying the Hodrick-Prescott (HP) filter. Second, we computed the analogous variance based on data simulated using all the shocks. The ratio of the two variances is our estimate of the fraction of business cycle variation due to monetary policy shocks.

The key finding is that the monetary policy shock accounts for only a trivial component of the data. For example, it accounts for only about 7.7 percent of the business cycle component of output. Of course, this is not to say that monetary policy is not important for understanding aggregate fluctuations. The nature of the monetary policy rule may be very important for determining the way the economy responds to non-monetary policy shocks. In addition, because the confidence intervals for the response to monetary policy shocks are fairly narrow, estimated responses to monetary policy shocks contain a substantial amount of information about the parameters of our equilibrium model. We will see this later on.

Table 1: Contribution of Monetary Policy Shocks to Variance

Variable	Forecast Variance at Indicated Horizon					Business Cycle Frequencies
	1	4	8	12	30	HP
Output	0.0	3.1	5.4	4.4	2.5	7.7
M2 Growth	6.2	6.5	6.0	5.4	5.1	7.0
Inflation	0.0	1.7	1.8	3.4	4.4	4.3
Fed Funds	65.2	21.0	12.5	11.0	9.1	20.3
Capacity Util	0.0	2.6	7.2	5.6	4.4	6.7
Average Hours	0.0	1.9	5.0	5.1	6.0	7.2
Real Wage	0.0	0.2	0.9	1.3	3.2	1.1
Consumption	0.0	3.3	2.6	1.6	1.4	6.0
Investment	0.0	2.8	5.4	4.8	4.6	7.3
Velocity	2.3	2.1	1.1	0.9	0.8	3.3

The percent of forecast error variance due to technology shocks is displayed in Table 2. Consider first the results pertaining to forecast error variances. The results indicate that technology shocks are an important source of variation in aggregate output. They account for nearly 50 percent of the forecast error variance at the 2 and 3 year horizons.[13] Two other

[13] Of course, as the forecast horizon increases this percent converges to 100 percent by construction.

notable features of the results are that technology play a substantial role in inflation, even at the 7 year horizon, and such a small role in hours and investment variation.

We now consider the results for business cycle frequencies. Two results stand out. First, technology shocks account for a surprisingly small amount of the variance in the business cycle component of output, employment and investment.[14] Second, technology shocks account for a surprisingly large amount of the business cycle variance in inflation.

Table 2: Contribution of Technology Shocks to Variance

Variable	Forecast Variance at Indicated Horizon					Business Cycle Frequencies
	1	4	8	12	30	HP
Output	48.4	48.8	47.1	45.7	62.7	13.7
M2 Growth	2.8	3.8	4.1	3.8	5.7	4.6
Inflation	41.1	32.1	28.5	25.8	17.4	20.9
Fed Funds	0.4	0.5	0.6	0.8	5.7	1.1
Capacity Util	1.4	9.7	8.2	5.3	4.5	3.2
Average Hours	4.1	15.6	19.3	17.2	11.2	5.0
Real Wage	27.7	32.1	35.6	36.9	44.8	16.4
Consumption	61.0	67.4	65.3	65.3	69.9	24.7
Investment	9.8	14.5	14.1	11.8	12.2	5.5
Velocity	11.4	3.0	1.7	2.2	3.7	4.7

Another way to assess the role of the identified monetary policy and technology shocks in driving the data, is presented in Figures 4-6. The thick line in Figure 4 displays a simulation of the 'detrended' historical data. The detrending is achieved like this. First, we simulated the estimated reduced form representation (3.1) using the fitted disturbances, $\hat{u}_t$, but setting the constant term, α, and the initial conditions of Y_t to zero. In effect, this gives us a version of the data, Y_t, in which any dynamic effects from unusual initial conditions (relative to the VAR's stochastic steady state) have been removed, and in which the constant term has been removed. Second, the resulting 'detrended' historical observations on Y_t are then transformed appropriately to produce the variables reported in Figure 4. The high degree of persistence observed in output in Figure 4 reflects that our procedure for computing it makes it the realization of a random walk with no drift.

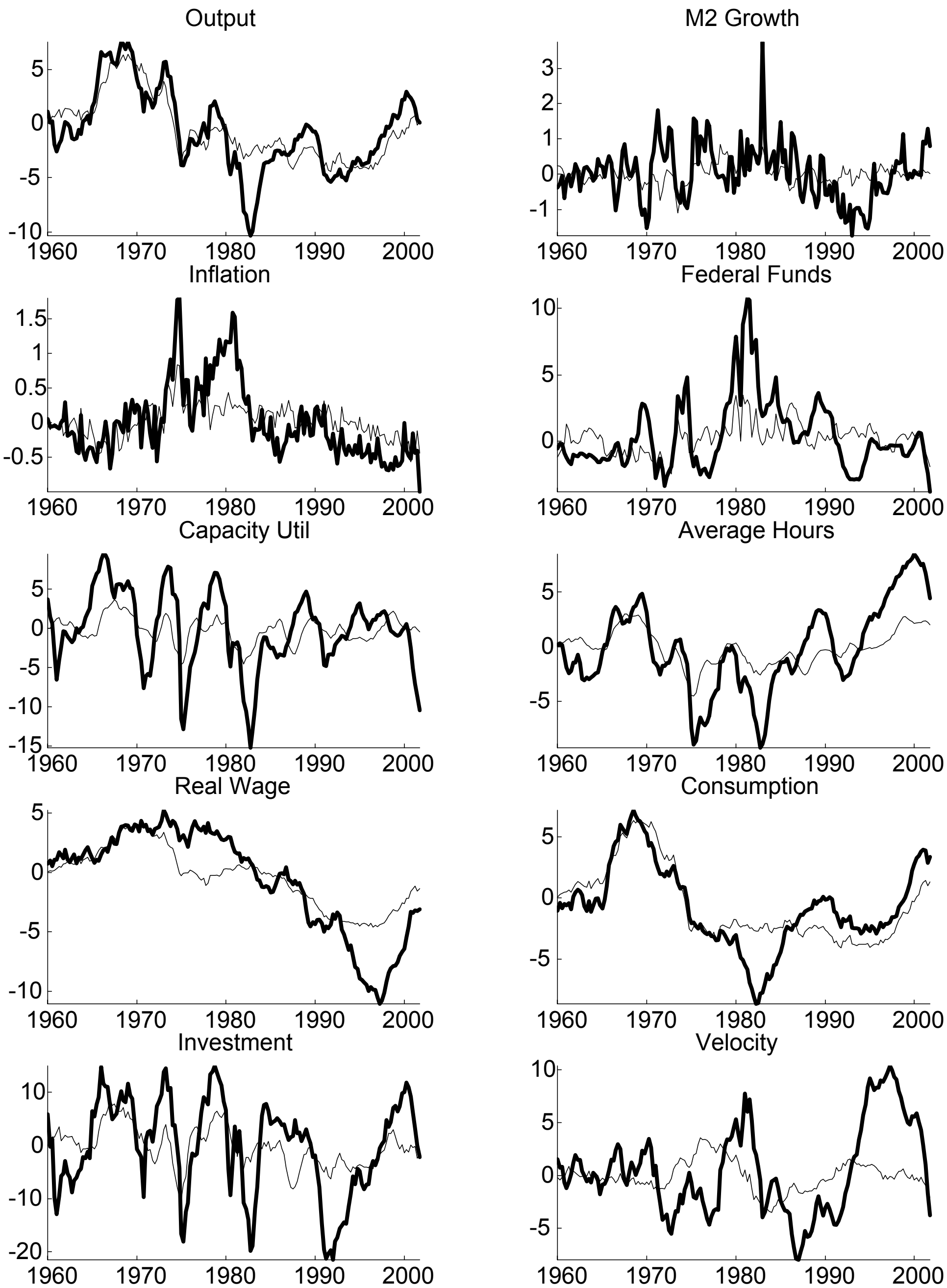
The procedure used to compute the thick line in Figure 4 was then repeated, with one change, to produce the thin line. Rather than using the historical reduced form shocks, $\hat{u}_t$, the simulations underlying the thin line use $C\hat{e}_t$, allowing only the 1^{st} and 8^{th} elements of

[14] In his discussion of an early draft of this paper, Adrian Pagan pointed out this feature of our estimated technology shocks, before we had noticed it.

$\hat{e}_t$ to be non-zero. Here, $\hat{e}_t$ is the estimated fundamental shocks, obtained from $\hat{e}_t = C^{-1}\hat{u}_t$. The results in Figure 4 give a visual representation of what is evident in Tables 1 and 2: our two shocks only account for about 50% of the fluctuations in the data.

Figure 4 also shows how well the shocks help to account for different frequencies of the data, as well as how well they work at accounting for the fluctuations in different subperiods. The shocks appear to do relatively well in the lower frequencies. In addition, technology and policy shocks together do well at accounting for the movements in output up to the late 1970s and in the late 1990s. These shocks to not account for much of the variation in the data in the 1980s.

Figure 4: Detrended Historical Data (Thick Line) Versus Component Due to Monetary Policy and Technology Shocks Alone (Thin Line)



Figures 5 and 6 allow us to see how well our two shocks work individually at accounting for the fluctuations in the data. The thin line in Figure 5 is the VAR's estimates of what history would have looked like if there had been only monetary policy shocks. Consistent with the results in Table 1, the monetary policy shocks account for only a trivial amount of the variation in the data.

Figure 5: Detrended Historical Data (Thick Line) Versus Component Due to Monetary Policy Shocks Alone (Thin Line)

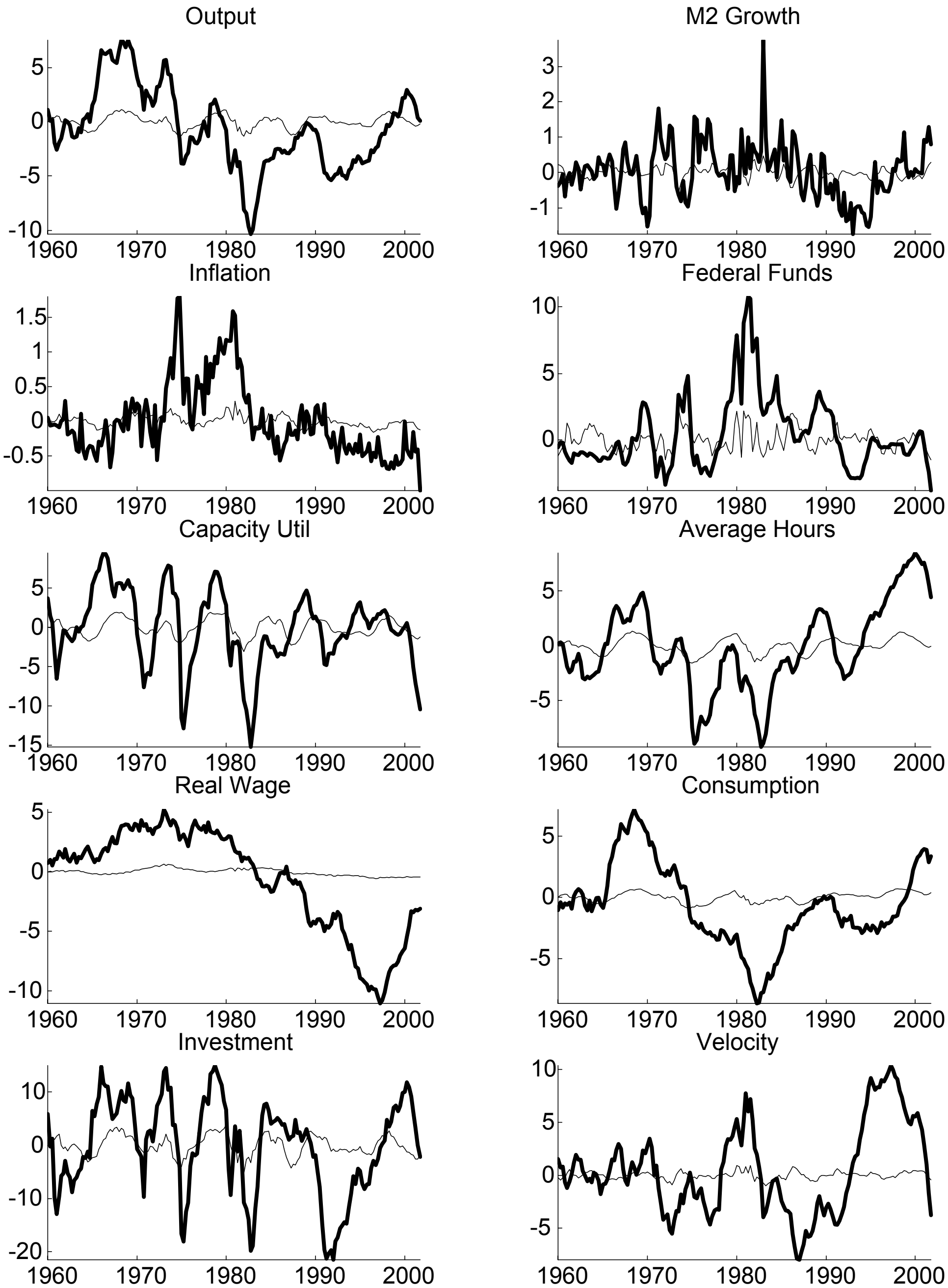
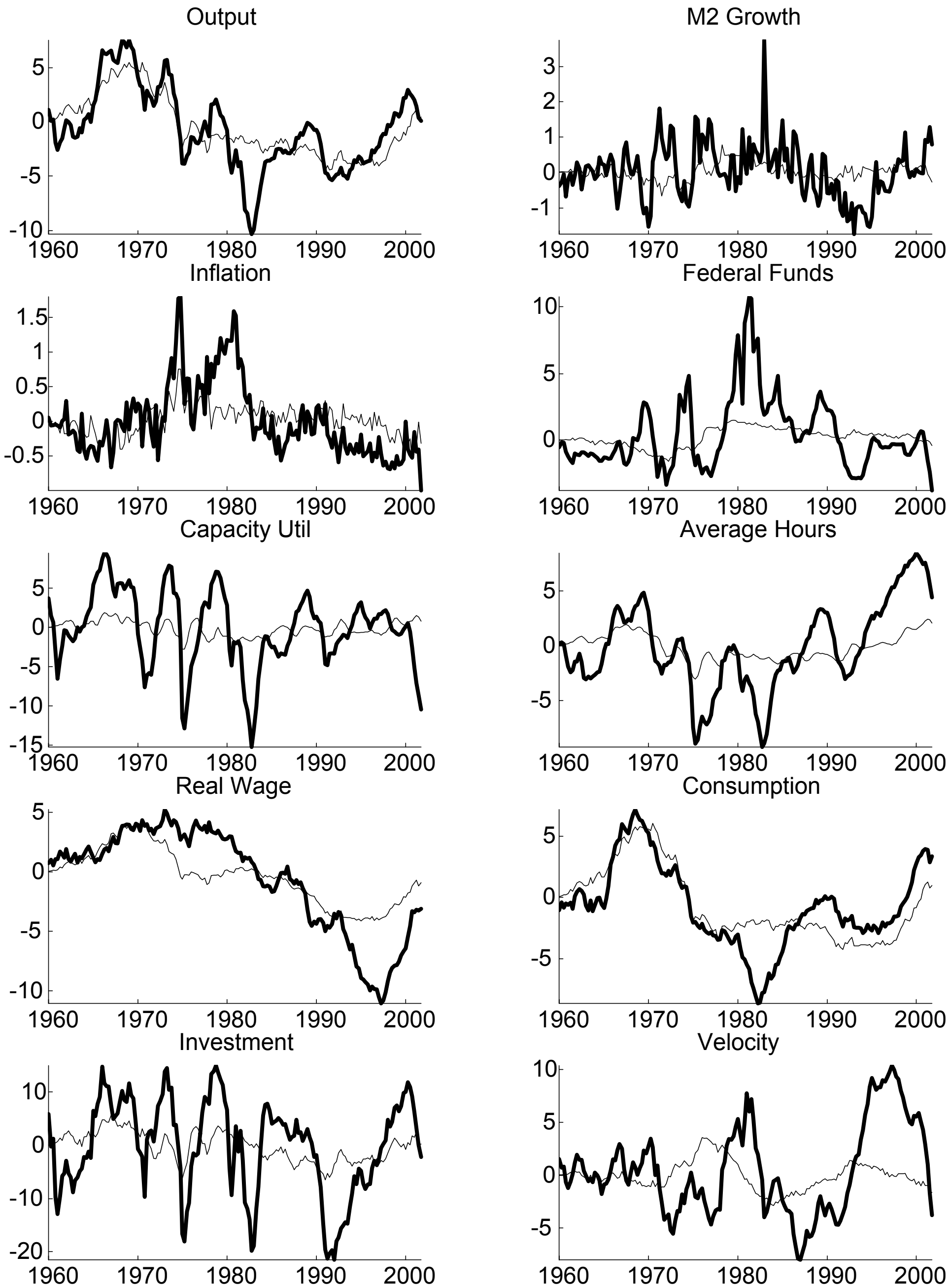


Figure 6 reports the analog of Figure 5, for the case of technology shocks. Consistent with the results in Table 2, the VAR analysis indicates that technology shocks account for a substantial portion of the fluctuations in the data. The portion of the data that it does best on, is the low frequency component. For example, technology shocks appear to play an important role in accounting for the rise and fall in output (relative to trend) before and after the 1970s, and the rise in the late 1990s. They also go a long way towards capturing the low frequency components of the consumption and investment data. Interestingly, it is not clear that technology has very much to do with the business cycle component in the data. Apart from the 1974 recession, technology shocks do not seem highly correlated with the major business cycle fluctuations. In particular, the simulations completely miss the 1970 recession, the recession in the early 1980s and the recession in the early 1990s.

Figure 6: Detrended Historical Data (Thick Line) Versus Component Due to Technology Shocks Alone (Thin Line)



To summarize, the evidence suggests that monetary policy shocks account for only a trivial part of the variation in the data, while technology shocks account for nearly 50 percent of the variation. Although the role of technology shocks appears to be quantitatively large, this role seems to be confined to explaining the relatively low frequency component of the data. In particular, technology shocks appear to play only a small role in triggering business cycle fluctuations. It is unclear at this point how to interpret this. A possibility is that technology shocks have two components. One component has a long run impact on productivity, and the other one has only a transitory impact. Our identification strategy, as we have implemented it so far, may be effective at picking up the first one and not the second.[15] In addition, it is possible that stationary technology shocks that are specific to the investment technology play an important role. They have not been included in our empirical analysis yet. So, it is still possible that technology shocks play an important role in driving the business cycle, if the driving force is stationary components of technology. As noted above, the analysis of this paper is being extended to other shocks, including a stationary shock to technology. When that analysis is completed we will hopefully have a more complete assessment of the role of technology shocks in business cycles.

Finally, it is interesting to note how the confidence intervals on the responses to technology are relatively wide by comparison with the corresponding confidence intervals for monetary policy shocks. This is particularly surprising in view of the fact that technology shocks appear to play a much more important role in economic fluctuations than monetary policy shocks. We suspect that the reason for this is fundamentally related to a weak instrument problem in our instrumental variables procedure for computing the response to technology shocks.

3.4. Related Literature

There is a growing literature, started by Gali (1999), which attempts to identify the dynamic effects of technology shocks using reduced form methods. In particular, Gali makes the assumption - which we have adopted in our analysis - that innovations to technology are the only disturbances that have an effect on the level of labor productivity in the long run. When he did this, he obtained results very different from the ones we reported above. He found that hours worked fall after a positive technology shock. The fall is so long and protracted that,

[15]We are still somewhat uncertain about the validity of this remark. To see what the issue is, consider the technology shock, $\epsilon_t (z_t)^{1-\alpha}$, in the intermediate good production function. This has a univariate representation, which has a unit root. We suspect that the analysis cannot distinguish between this univariate representation and the two univariate representations separately, other than via the restrictions we have placed on the time series representations of ϵ_t and z_t.

according to his estimates, technology shocks are a source of negative correlation between output and hours worked. Reasoning from the observation that hours worked in fact are procyclical, Gali concluded that some other shock or shocks must be playing the predominant role in business cycles. Thus, he concludes that technology shocks at best play only a minor role in fluctuations. Moreover, he argues that standard real business cycle models shed little light on whatever small role they do play, because they do not generally imply a protracted fall in employment after a positive technology shock. In effect, real business cycle models are doubly dammed: they address things that are unimportant, and they do it badly at that. Other recent papers reach conclusions that complement Gali's in various ways (see, e.g., Shea (1998), Basu, Kimball and Fernald (1999), and Francis and Ramey (2002).) In view of the important role played by technology shocks in business cycle analyses of the past two decades, Francis and Ramey perhaps do not overstate too much when they say (p.2) that Gali's argument is a '...potential paradigm shifter'.

Our results differ from those in the literature in that our point estimates imply a rise in hours after a policy shock. Confidence intervals are wide, so the disagreement is not as sharp as the point estimates themselves suggest. Still, there is disagreement. Regarding the importance of technology shocks in the cycle, our results so far are qualitatively consistent with Gali's view that they are not important. However, for the reasons noted above, Gali's conclusion may not survive our analysis when we extend it to include other types of shocks to technology.

The remainder of this section reports on our efforts to understand why we find that hours rises after a technology shock, while others (primarily, Gali and Francis-Ramey) find that it falls. The difference in results is perhaps surprising, since their fundamental identification assumption - that shocks to technology are the only shocks that have a long-run impact on labor productivity - is also adopted in our analysis. Still, there are a variety of differences between our VARs and those used by Gali and Francis-Ramey. One difference is that the number of variables used in the analysis differs. They tend to work with VARs with fewer variables. So, one possibility is that their analyses suffer from omitted variables bias. Another difference is that we include the (log) level of hours worked in Y_t, while Gali and Francis-Ramey tend to work in terms of the first difference of this variable. From the point of view of our model, in which hours worked is stationary, first differencing is over-differencing. So, to model Y_t as a VAR with the growth rate of hours worked would constitute a specification error from the standpoint of our model.[16]

Our preliminary results suggest that distortions due to omitted variables are the primary reason for the difference in results. Overdifferencing plays a role as well, though to a smaller

[16]To see this, note that overdifferencing induces a moving average error with a unit root. There does not exist a finite-lag, VAR representation for such a variable.

extent.

The remainder of this section is divided into three parts. First, we consider the impact of modeling hours in terms of levels or growth rates in our VAR system. We find that under the hypothesis that the levels specification is the right one, then differencing hours leads to an understatement of the employment response to a technology shock. We argue on statistical grounds that the level specification of our VAR is more plausible than the difference specification. The second subsection below shows how omitted variables can result in a negative response of employment to a technology shock even when the true response is positive. The third section considers subsample stability. The analysis throughout this paper assumes the data are drawn from a single time series representation throughout the sample. However, based on examining point estimates, Gali, Lopez-Salido, and Valles (2002) argue that there has been a substantial break in the sample. We perform formal tests of stability based on the approach in Christiano, Eichenbaum and Evans (1999) and tentatively find that the evidence against stability is not persuasive.

3.4.1. Levels Versus Differences of Hours Worked

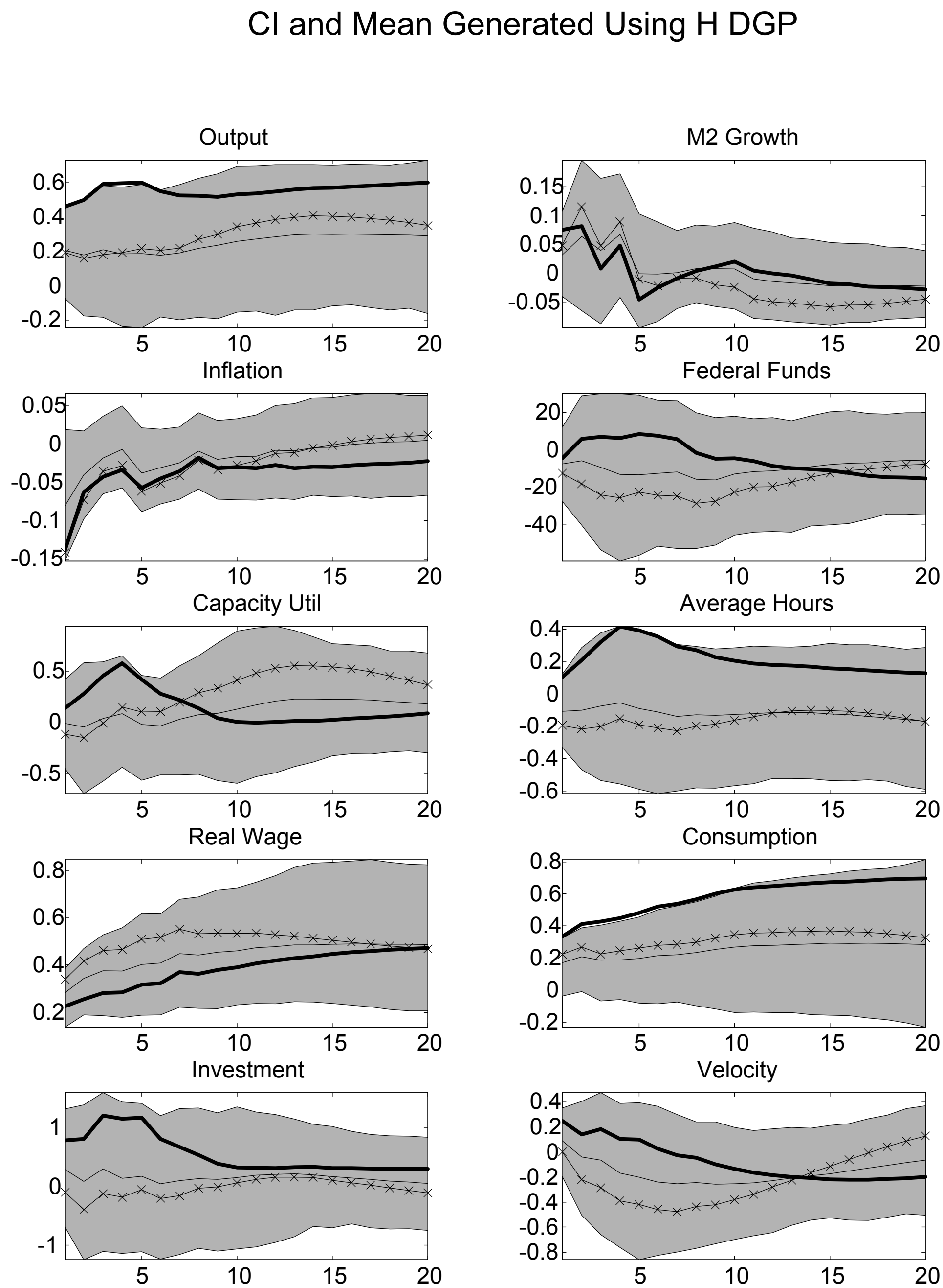
When we redo our analysis by replacing log hours in Y_t with its first difference, then we obtain results like those of Gali and Francis-Ramey. That is, we find that hours worked decline after a positive monetary policy shock. The results are presented in Figure 7. The lines indicated by x's in each panel indicate our point estimates. Note how the response in hours worked is negative for each of the 20 quarters of responses shown. For comparison, the thick dark line in Figure 7 reproduce our baseline point estimates displayed in Figure 3 (we discuss the other lines momentarily). Under our assumption about hours worked, the VAR estimated by Gali and Francis-Ramey is misspecified because hours worked are over-differenced.

We investigated whether the decline in hours worked after a positive technology shock could reflect distortions due to over-differencing. We find that it can. We determined this by generating numerous samples of artificial data from our estimated VAR in which hours appears in level form in Y_t. In each artificial data sample, we fit a misspecified version of our VAR in which hours worked appears in growth rate form. We then computed the impulse responses to a technology shock. The mean impulse responses appear as the thin line in Figure 7. The gray area represents the 95 confidence interval of the simulated impulse response functions.[17] The key thing to note is that hours worked on average declines in

[17] That is, for each lag we ordered the impulse responses from smallest to largest. The confidence interval is defined by the interval from the 25^{th} element in this ranking to the 975^{th} element (the number of data sets that were simulated is 1000.)

response to a positive technology shock in the simulated data. That is, our level specification attributes the decline in hours in the estimated VAR with differenced hours data to overdifferencing.

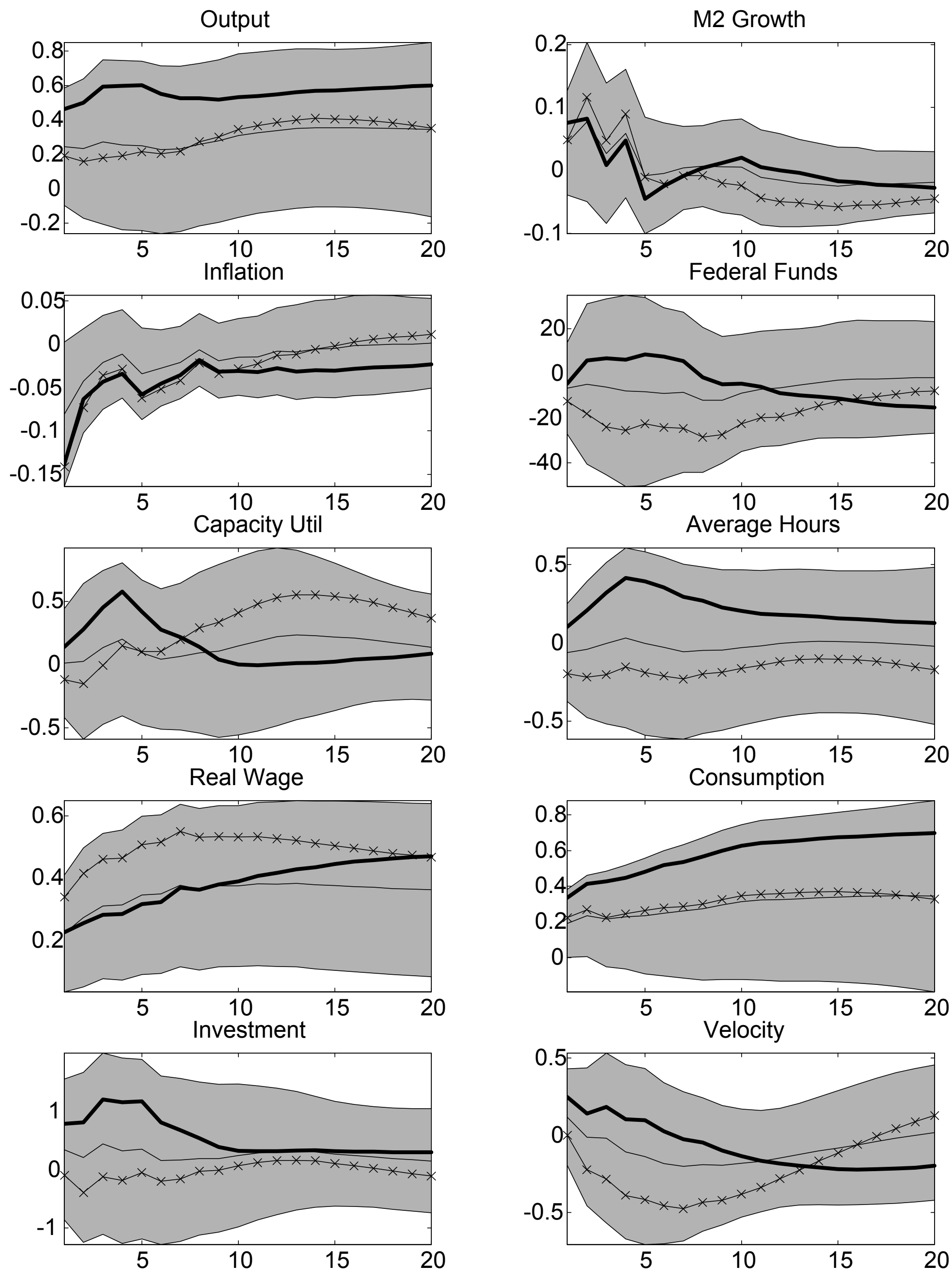
Figure 7 Response of Variables to Technology Shock
Data Generating Mechanism: VAR in Level of Hours



Notes:
Thick Line - Baseline Point Estimates Based on VAR with Level Hours (Figure 3)
X's - Point Estimates Based on VAR with Log First Difference Hours.
Thin line - Average Responses, Impulse Responses Computed From VAR with Log First Difference of Hours, in Artificial Data Generated from Baseline VAR.

We also did the reverse test: can the VAR with hours growth attribute the estimated rise in hours in our benchmark model to some sort of distortion resulting from the fact that we specified hours in levels? On a priori grounds, this possibility seems unlikely since specifying hours in levels when it should have been in differences is not really a specification error, as the VAR can accommodate differencing simply by incorporating a unit root. Still, we are open to the possibility that small sample problems deriving from not imposing a unit root when it is appropriate could account for our benchmark finding that hours rises after a positive technology shock. The results of this investigation are reported in Figure 8. The thick, solid line and the line composed of x's reproduce the analogous lines from Figure 7 for convenience. The thin line in Figure 8 is the prediction of the VAR with hours in first differences for the impulse responses one obtains with a VAR with hours in levels. The gray area is the associated confidence interval. The notable thing about these results is that the thin solid line is negative at all lags displayed. That is, the distortion from not imposing the unit root is not large enough to account, on average, for the actual finding with our estimated benchmark model that hours worked rises. At the same time, there is a wide confidence interval about the thin line, which includes the thick, solid line. So, the difference results could explain our benchmark results as reflecting the effects of sampling uncertainty.

Figure 8: Response of Variables to Technology Shock
Data Generating Mechanism: VAR in First Difference of Hours



Notes
Thick Line - Baseline Point Estimates Based on VAR with Level Hours.
X's - Point Estimates Based on VAR with Log First Difference Hours.
Thin line - Average Responses, Impulse Responses Computed From VAR with
Log Level Hours, in Artificial Data Generated from VAR with First Difference Hours.

We conclude this discussion by asking, which results are more plausible, the ones based on differences in hours, which imply that employment drops persistently after a technology shock, or the ones based on our benchmark results? We address this question by computing the sort of posterior odds ratio computed in Christiano and Ljungqvist (1988) for a similar situation where differences and levels of data lead to very different inferences about some statistic. The basic idea is that the more plausible of the two VAR's is the one that has the easiest time explaining the facts: that the VAR in levels implies hours rises and the VAR in differences implies hours falls, after a technology shock.

To proceed, it is convenient to summarize the findings for hours worked in the form of a scalar statistic. We choose to work with the correlation between the 20-quarter ahead forecast uncertainty in output and hours worked.[18] Our benchmark levels VAR implies that this correlation, ρ^L, is above 0.85, while the VAR in which hours worked appears in first difference form implies this correlation, $\rho^{\Delta L}$, is roughly -0.85. We simulated 1,000 artificial data sets using each of our two estimated VARs as data generating mechanisms. In each data set, we calculated $(\rho^{\Delta L}, \rho^L)$ using the same method used to compute these statistics in the actual data.

The results are reported in Figures 9a and 9b. In each case, the header indicates the underlying data generating mechanism. The horizontal axis corresponds to $\rho^{\Delta L}$, while the vertical axis corresponds to ρ^L. The red square indicates the empirical estimate of $(\rho^{\Delta L}, \rho^L)$, $(\hat{\rho}^{\Delta L}, \hat{\rho}^L)$. The yellow square indicates the average across artificial data sets, of $(\rho^{\Delta L}, \rho^L)$. Each dot represents a realization of $(\rho^{\Delta L}, \rho^L)$ in artificial data generated by the VAR indicated in the figure header.

[18] Let h and y denote the first 20 quarters' response of log hours and log output, respectively, to a technology shock. The correlation we studied is computed like this: $(h'y) / \sqrt{(h'h)(y'y)}$.

Figure 9a:
Correlations From Benchmark VAR

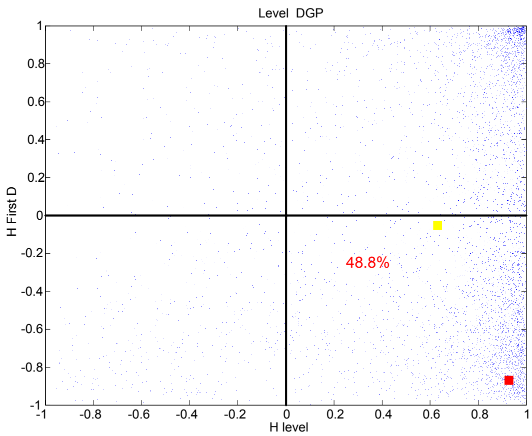
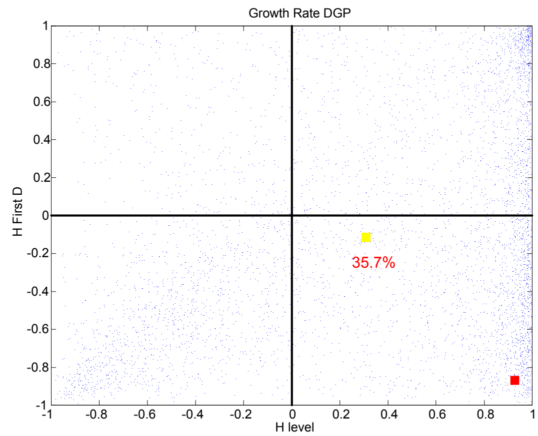


Figure 9b:
Correlations From VAR with First-Differenced Hours



In comparing the two figures, we see that Figure 9b assigns relatively more density to the bottom left quadrant: the one in which both correlations are negative. The figures suggest that the benchmark VAR has a relatively easier time explaining the observed values of $(\rho^{\Delta L}, \rho^{L})$, $(\hat{\rho}^{\Delta L}, \hat{\rho}^{L})$. To quantify this, the percent of artificial $(\rho^{\Delta L}, \rho^{L})$'s with $\rho^{\Delta L} < 0$ and $\rho^{L} > 0$ is 48.8 in the artificial data generated by the benchmark VAR, while it is 35.7 for the VAR with first differenced hours. That is,

$$\begin{aligned} P(Q|A) &= 0.49 \\ P(Q|B) &= 0.36, \end{aligned}$$

where Q denotes the event, $\rho^{\Delta L} < 0$ and $\rho^{L} > 0$, A indicates the benchmark model, B indicates the VAR model with first differenced hours, and P denotes probability. Suppose that our priors over A and B are equal: $P(A) = P(B) = 1/2$. The unconditional probability of Q, $P(Q)$, is $0.49 \times 0.5 + 0.36 \times 0.5 = 0.43$. Probability of the two models, conditional on having observed Q, is:

$$\begin{aligned} P(A|Q) &= \frac{P(A,Q)}{P(Q)} = \frac{P(Q|A)P(A)}{P(Q)} = 0.57 \\ P(B|Q) &= 0.43. \end{aligned}$$

So, we conclude that given the observations, the odds favor our benchmark model over the model with first differenced hours by 1.3 to one. They favor the benchmark model slightly.

Fundamentally, this is because the benchmark model has an easier time explaining $(\hat{\rho}^{\Delta L}, \hat{\rho}^{L})$ than does the other model. On these purely statistical grounds we argue that the benchmark model and its implications are more 'plausible' than those of the other VAR.

3.4.2. Omitted Variables Bias

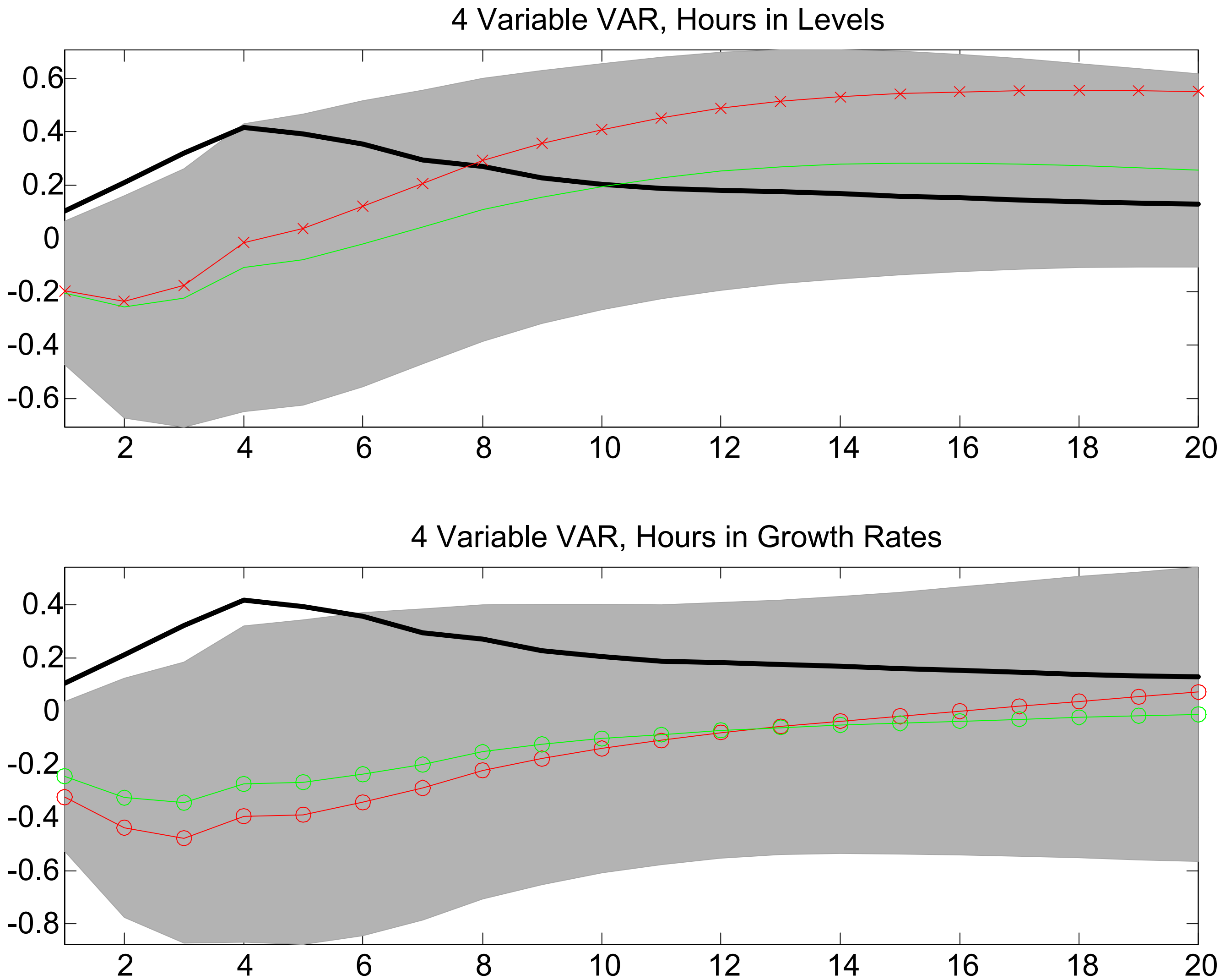
We now investigate the consequences for estimating the response of employment to a technology shock, of working with a small VAR. To illustrate the possibilities, we study a four variable VAR like the one analyzed by Gali, Lopez-Salido, and Valles (2002). The VAR includes our measures of productivity growth, hours worked, the interest rate and inflation. We estimate the four variable VAR over our sample period, 1959 - 2001, under two different treatments of hours worked. In the first, we include the log level of hours worked. This allows us to focus just on the consequences of omitting variables.[19] In the second, we include the first difference of log hours worked. This allows us to focus on the simultaneous consequences of omitting variables and first differencing. In each case, we use the same long-run restrictions used in the 9 variable analysis to identify technology shocks.[20] The results are

[19]From the perspective of our benchmark VAR, the variables omitted are capacity utilization, the real wage, consumption, investment and $M2$.

[20]We do not also impose on the 4-variable VAR the restrictions implied by our recursiveness assumption on monetary policy. The literature on the dynamic effects of technology shocks does not at the same time estimate the effects of monetary policy shocks, as we do here.

reported in Figure 10:

Figure 10: Analysis of Two Versions of Four-Variable VAR



In both panels of Figure 10, the thick solid line is our estimate of the response of hours worked to a technology shock. This is simply taken from Figure 3. We now discuss the top panel of the figure. Here, the line with x's indicates the point estimates of the response in hours worked to a technology shock, when the 4 variable VAR is estimated with hours worked specified in levels. Note the implication of the point estimates that hours drop for about one year after a positive technology shock. The thin, continuous line in the figure is the small sample expected value corresponding to the line with x's, conditional on our estimated 9 variable benchmark model being true. To obtain this expected value, we simulated 1,000 artificial data sets from our estimated benchmark VAR. In each artificial data set we performed the same set of calculations that produced the line marked with x's. That is, we fit the 4 variable VAR and used it to estimate the response of hours worked to a technology shock. The thin line is the average impulse response across the 1,000 data sets. The gray area is a 95% confidence interval about the thin line. According to our benchmark model, hours in fact rise after a shock to technology (thick line) and the drop estimated in the 4 variable VAR just reflects the effects of omitted variables bias.

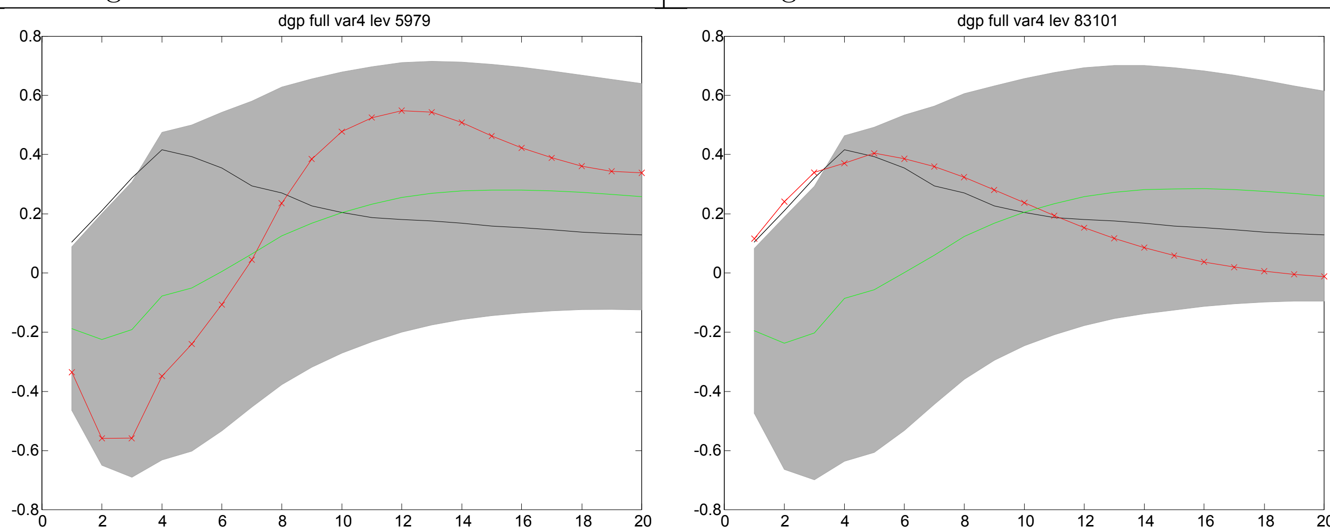
Now consider the bottom panel in Figure 10. There are two lines with circles. The lowest one at low lags is the estimated response of hours worked in the version of the four variable VAR in which hours appear in first difference form. The other line with circles is the expected value of the estimates, conditional on our benchmark model being true. The gray area is the associated 95 % confidence intervals. There are two things of interest here. First, as in the top panel of Figure 10, according to the benchmark model the estimated decline in hours worked implied by the 4 variable system reflects distortions. The actual response in the simulations is positive (thick line). Second, the magnitude of the distortions is substantially larger in the right panel than in the left, consistent with the notion that omitted variables and overdifferencing both drive the estimated response of hours worked down. Our estimates suggest that the bias at lag 0 due to omitted variables is about 0.3 percentage points. Distortions due to overdifferencing add another 0.1 percentage point, or so. After a lag of a few quarters, the distortions are substantially larger.

3.4.3. Subsample Stability

A recent paper by Gali, Lopez-Salido, and Valles (2002) shows that estimated impulse response functions change substantially between the pre-Volcker and post Volcker-Greenspan sample periods. To see this, consider results in Figure 11, which are based on the 4-variable VAR with hours specified in first differences. First, for convenience each panel in this figure reproduces the response of employment to a technology shock estimated from our benchmark system. In addition, each figure has a line with x's, which indicates point estimates obtained using the 4-variable system. The left panel reports results for the pre-Volcker period and the right panel presents results for the post-Volcker period. Finally, the solid line in the middle of the gray area is the average impulse response function for the indicated sample, implied by 1,000 simulations of our benchmark VAR. It is what our benchmark VAR predicts will happen in the indicated subsample, when the 4 variable system is estimated. The gray area is the associated 95% confidence interval.

There are two things worth noting in these figures. There is indeed a substantial change in the estimated impulse response function. Between pre- and post- Volcker periods, the impulse response functions switch from negative to positive. However, the gray area is quite wide and the change in parameters is at best marginally significant. Moreover, note that the difficulty we have comes from a surge in employment in the late period. In the early period the decline in employment is fully consistent with the hypothesis of omitted variable bias and the idea that employment actually rises.

Figure 11: Analysis of Results for the 4-Variable VAR With Hours in First Differences	
Figure 11a: Pre-Volcker - 1959-1979	Figure 11b: Post-Volcker - 1983-2001



We conclude that the evidence of subsample instability is at best marginal.[21] Moreover, whatever evidence of instability there is does not appear to pose a challenge to the proposition, incorporated in our benchmark VAR, that employment responds positively to a technology shock. Our analysis is not yet fully complete, and we still need to perform a stability test for our benchmark model. This is currently underway.

[21] We also performed the test underlying those in Figure 11 using the full-sample estimated 4-variable VAR as the data generating mechanism. This procedure did not even find marginal evidence against stability. In addition, we repeated the analysis for the 4- variable VAR specified in terms of the level of hours. Here, there was not even much instability in terms of point estimates.

4. Results

This section reports our parameter estimates and diagnoses model fit by evaluating how well the model's impulse responses match those estimated in the data.

We divide the parameters into those whose values are estimated here and those whose values are taken from elsewhere. The latter are reported in Table 1. For the most part, the values used are standard. The parameter governing market power of household labor suppliers, λ_w, is arbitrarily set to 1.05. In future drafts, we plan to include this parameter in the list of parameters to be estimated.

Table 1: Parameters that Do Not Enter Formal Estimation Criterion

discount factor	β	$1.03^{-.25}$
capital's share	α	0.36
capital depreciation rate	δ	0.025
markup, labor suppliers	λ_w	1.05
mean, money growth	μ	1.017
labor utility parameter	ψ_0	set to imply $L = 1$
real balance utility parameter	ψ_q	set to imply $Q/M = 0.44$
fixed cost of production	ϕ	set to imply steady state profits $=$ 0

The 13 model parameters that we estimate here are:

$$\gamma \equiv (\lambda_f, \xi_w, \xi_p, \sigma_q, S'', b, \sigma_a, \text{6 parameters governing exogenous shocks}).$$

As a reminder, $\lambda_f \geq 1$ is the markup set by monopolist intermediate good suppliers, ξ_w is the probability that a household cannot reoptimize the wage for its differentiated labor service, ξ_p is the probability that the monopoly supplier of a differentiated intermediate good cannot reoptimize its price, σ_q is a curvature parameter related to money demand, S'' is a curvature parameter related to adjustment costs on investment, b is the habit parameter, and σ_a is the parameter controlling the curvature on costs of capital utilization. The list of 'parameters governing monetary policy and technology' are simply the parameters in () and (2.3).

Corresponding to each γ, we compute a set of model impulse response functions, $\psi(\gamma)$. Denote the impulse response functions for the data by $\hat{\psi}$. This is the list of numbers reported in Figures 2 and 3.[22] We have not yet implemented our procedure for also estimating the other shocks.[23] So, the vector, $\hat{\psi}$, summarizes the first 20 lags in the response function of our 9 variables to technology and monetary policy. Our estimator of γ minimizes the distance between $\psi(\gamma)$ and $\hat{\psi}$:

$$\hat{\gamma} = \arg\min_{\gamma}(\hat{\psi} - \psi(\gamma))' V^{-1}(\hat{\psi} - \psi(\gamma)),$$

where V is the diagonal matrix composed of our estimate of the sample standard deviation in $\hat{\psi}$. Essentially, our estimation procedure tries to get the model's impulse responses as close to the thick line in Figure 2 and 3. It pays most attention to impulses were the gray area is the thinnest. We computed standard errors for the estimated values of γ using the usual delta function method.

The results are reported in the following two tables. Table 2 reports the values of the economic parameters, while results for the parameters of the exogenous shock processes are reported in Table 3.

---

[22]There are 360-6 elements in $\hat{\psi}$: nine variables, 20 lags and 2 shocks. We subtract 6 from the total to take into account the 6 variables whose contemporaneous responses to a monetary policy shock are assumed to be zero under our identifying assumptions.

[23]We do have some intriguing, preliminary results. With model-based estimation, a subset of the elements of $\hat{\psi}$ is a function of unknown parameters: the elements of the 6 dimensional orthonormal matrix, w, discussed in section 3.2.2. We began model-based identification, by working with one shock in e_{1t} alone. We interpreted the first element of e_{1t} as the shock to the preference for leisure (or, to labor market power). The only part of w that is relevant for this is w_1, the first column (so, the only restriction to implement is that the length of w_1 be unity). Let the subset of $\hat{\psi}$ that corresponds to the dynamic response to a leisure shock be denoted $\hat{\psi}'(w_1)$. We attempted to estimate $\hat{\psi}'(w_1)$ by minimizing its distance from the corresponding part of $\psi(\gamma)$, which we denote by $\psi'(\gamma)$. Regardless of starting values, the estimation procedure always chose w_1 and the variance of the preference shock in the model to make $\hat{\psi}'(w_1)$ and $\psi'(\gamma)$ close to zero.

We conjecture that this finding reflects a problem with estimating just one element in a list of several shocks, by our model-based approach. To see the problem, recall the finding in the existing literature on dynamic factor analysis, which suggests that a small number of shocks account for a large amount of the variation in the data. A corollary of this is that a large number of shocks explain very little. Apparently, our model-based procedure, when applied to only one shock out of potentially several, undertakes a 'race to the bottom', by choosing w_1 to produce the shock with *least* variance. In effect, the distance between $\hat{\psi}'(w_1)$ and $\psi'(\gamma)$ is minimized by setting each close to zero (setting $\hat{\psi}'(w_1)$ exactly to zero is impossible, since that would be inconsistent with Y_t having full rank). We suspect that rather than just estimating one shock among the six, one of two alternative courses of action must be followed. Either estimate six shocks, or compute the principle component shocks and if one wants to estimate $x < 6$ shocks, do so using the x principle component shocks as a basis.

We divide our discussion into three parts. We begin with the benchmark estimation results, in which γ is chosen to make the model match all the impulses simultaneously. To gain an understanding for the role played by impulse responses to technology and to policy in the results, we perform two other analyses. First, we re-estimate γ by including only responses to policy shocks in the estimation. Then, we re-estimate γ by including only responses to technology shocks. In each of these two cases, we must delete from γ the components pertaining to the impulses not included.

4.1. Benchmark Results

We now turn to the benchmark estimation. The first row of Table 2 exhibits the resulting model parameter values. Our impression is that these are all reasonable. The estimated value of λ_f implies a steady state markup of 14 percent. The estimated value of ξ_w implies that wage contracts last on average a little over 4 quarters, while the estimated value of ξ_p implies that price contracts last a little under 2 quarters. By comparison with existing survey evidence on the degree of sticky wages and prices, our estimated amount of stickiness is quite modest. The habit parameter, b, is very similar to the value used in Boldrin, Christiano and Fisher (2001), using a non-monetary version of the model here, to match basic asset pricing facts such as the equity premium.

Table 2: Estimated Economic Parameter Values (Standard Errors)

Estimation Based Estimated Responses to:	λ_f	ξ_w	ξ_p	σ_q	S''	b	σ_a
Policy and Technology Shocks Simultaneously	1.14 (.016)	.78 (0.04)	.42 (0.12)	14.13 (1.74)	7.69 (1.33)	0.73 (0.07)	0.05 (0.01)
Policy Shocks Only	1.15 (0.27)	0.73 (0.03)	0.45 (0.06)	12.33 (0.61)	9.97 (3.36)	0.77 (0.04)	0.03 (0.01)
Technology Shocks Only	1.65	0.99	0.08	18.67	20.00	0.60	0.02

The estimated parameters of the exogenous shocks for the benchmark run are reported in the first column of Table 3. The first order autocorrelation of the growth rate of technology is estimated to be 0.80. The standard deviation of the innovation is 0.12 percent. This corresponds to an overall unconditional standard deviation of 0.2 percent for the growth rate of technology. These results differ somewhat from Prescott (1986), who estimates the properties of the technology shock process using the Solow residual. He finds the shock is roughly a random walk and its growth rate has a standard deviation of roughly 1 percent.[24] Our results are potentially consistent with Prescott's findings, for three reasons. First, we

[24] Prescott (1986) actually reports a standard deviation of 0.763 percent. However, he adopts a different normalization for the technology shock than we do, by placing it in front of the

model technology shocks as having two components, a temporary one and a permanent one. The analysis up to now has only included the permanent one. Second, from the perspective of our model, Prescott's estimate of technology confounds technology with variable capital utilization. Both these factors may explain why our technology shock standard deviation is one-fifth the size of Prescott's. They may also explain why we find so much more persistence. A more conclusive finding on this dimension awaits our analysis of the model with the additional shocks.

According to the estimates in Table 3, monetary policy responds immediately to a positive realization of the technology shock. For every one percent innovation in technology, the money stock jumps by 2 percent, according to the point estimates. At the same time, the standard error on this parameter is estimated particularly imprecisely, with a standard error of 1.17. The autoregressive parameter on the response of money to technology indicates that money growth increases not just in the period of a technology shock, but jumps again in the period afterward.

We now consider the results in Table 3 pertaining to monetary policy shocks. These indicate that a monetary policy shock drives up the money stock by 0.11 percent, with an extremely tight standard error. The increase in money growth is autocorrelated over time.

Table 3: Estimated Parameters of Exogenous Shock Processes

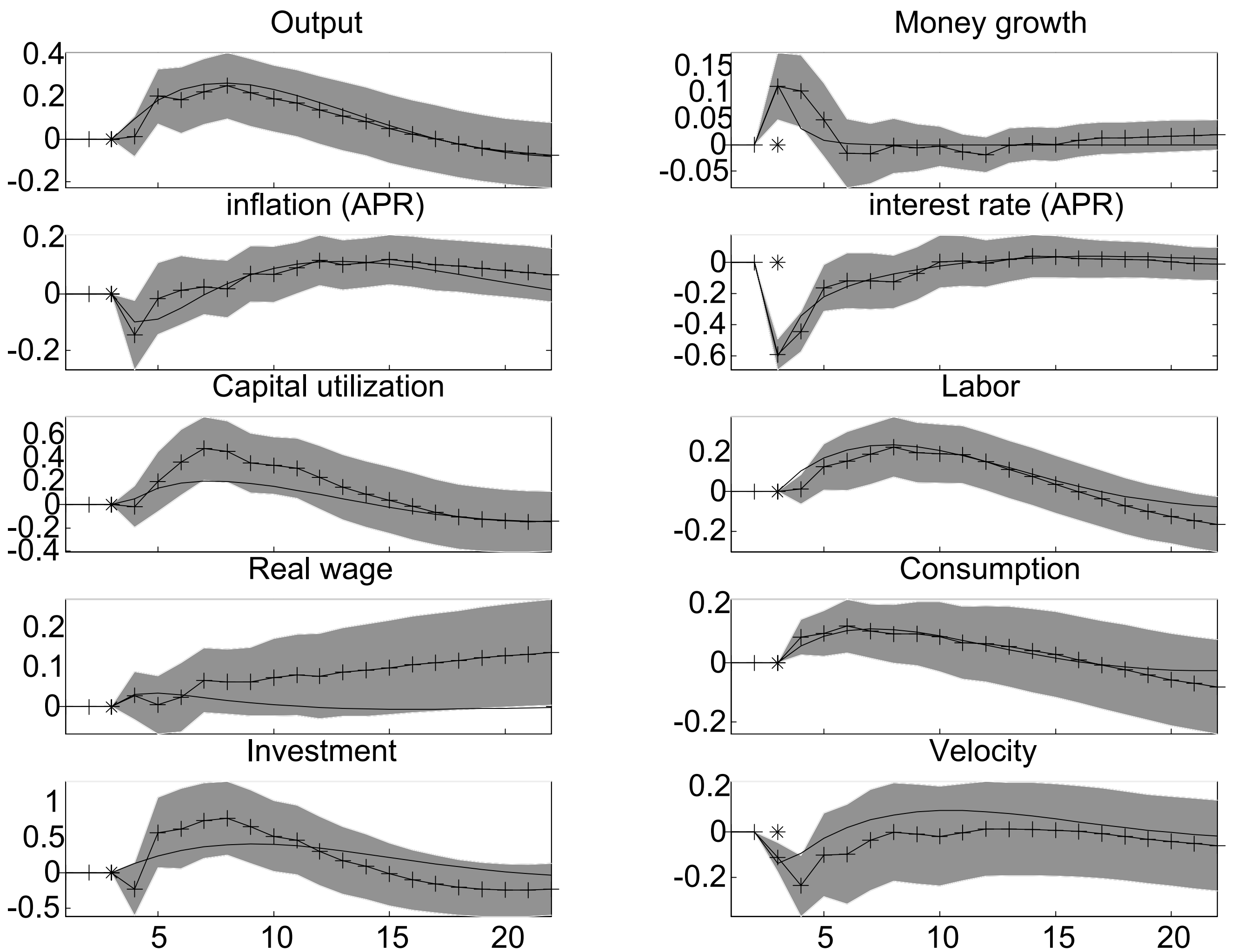
	Estimation Based on Estimated Responses to:		
	Policy and Technology	Policy	Technology
Parameter	Shocks Simultaneously	Shocks Only	Shocks Only
ρ_x	0.80 (0.11)	na	0.92
σ_{ε_x}	0.12 (0.06)	na	0.05
ρ_{μ_x}	0.47 (0.10)	na	0.29
c_{μ_x}	2.07 (1.17)	na	3.59
ρ_{μ_p}	0.27 (0.07)	0.27 (0.10)	na
$\sigma_{\varepsilon_{\mu_p}}$	0.11 (0.005)	0.13 (0.01)	na

Figures 12 and 13 display the dynamic response of the model variables (see the continuous lines) at the estimated parameter values. The period of the shock is indicated by a '*'. For convenience, we have included the empirical impulse responses (see the lines marked by '+') and 95% confidence intervals (see the grey areas) estimated in the data and reported in

production function. Instead, our technology shock multiplies labor directly in the production and is taken to a power of labor's share. The value of labor's share that Prescott uses is 0.70. When we translate Prescott's estimate into the one relevant for our normalization, we obtain $0.763/.7 \approx 1$.

Figures 2 and 3. In our view, the fit is very good. The response of capital utilization is slightly weak, though still inside the confidence intervals everywhere. Velocity misses the confidence interval very slightly in the period after the shock.

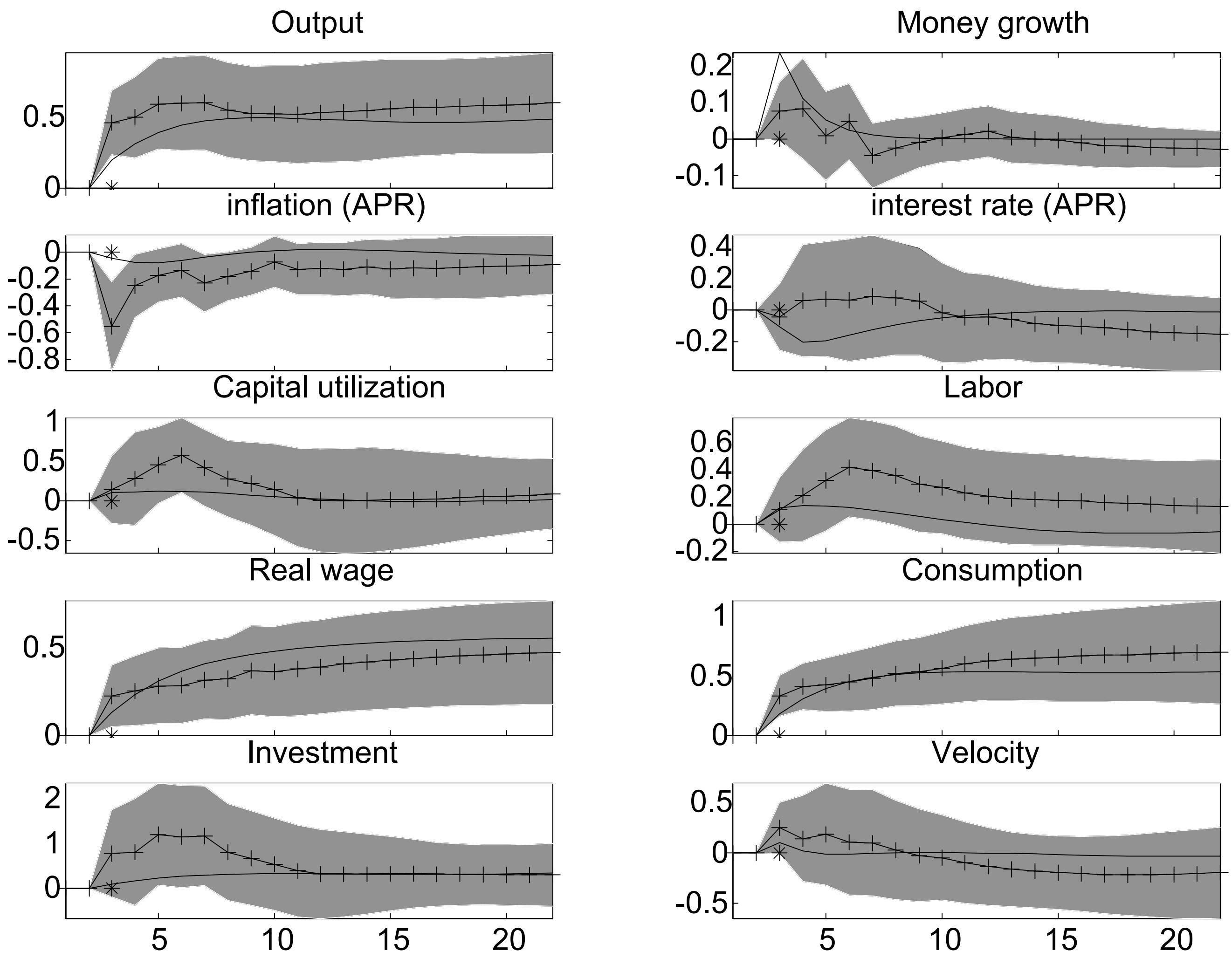
Figure 12: Properties of Benchmark Estimated Model - Dynamic Response to Monetary Policy Shoc



Now consider the responses to a technology shock, reported in Figure 13. Here too the model mimics the impulse responses in the data reasonably well. However, it is easier to find fault with the model in Figure 13 than it is in to do so in Figure 12. Inflation in the model does not quite fall enough, and the response in capital utilization, labor and output is somewhat on the weak side. Finally, the response of money growth is too strong.

Figure 13: Properties of Benchmark Estimated Model - Dynamic Response to Technology Shock

Figure 2: Model and Data Impulse Response Functions to a Non-stationary Technology Shock



To better understand the reasons for these estimation results, we turn to estimation based on only policy and technology shocks, in the next two subsections.

4.2. Estimation Based on Policy Shocks Alone

We can obtain insight into what is driving the results by considering what happens when model parameters are estimated using only the impulse responses to a monetary policy shock. For this experiment, the parameters governing the univariate representation of the technology shock and the parameters governing the response of monetary policy to technology were held fixed at the benchmark estimates. A notable feature of the results, is that there is little difference. For example, the estimated parameter values in Tables 2 and 3 are very similar for the benchmark run, and the run pursued here. In terms of the responses to a policy shock, the improvements are nearly imperceptible. Similarly, in terms of the response to technology shocks, the deterioration in the performance of the model is quite small. This can be seen by comparing the results in Figure 15 with those in Figure 13. It appears that the benchmark estimation results have been driven by the empirical estimates to a monetary policy shock, and that those estimates work reasonably well for the response of technology shocks too.

Figure 14: Properties of Model Fit to Policy Impulse Responses Only

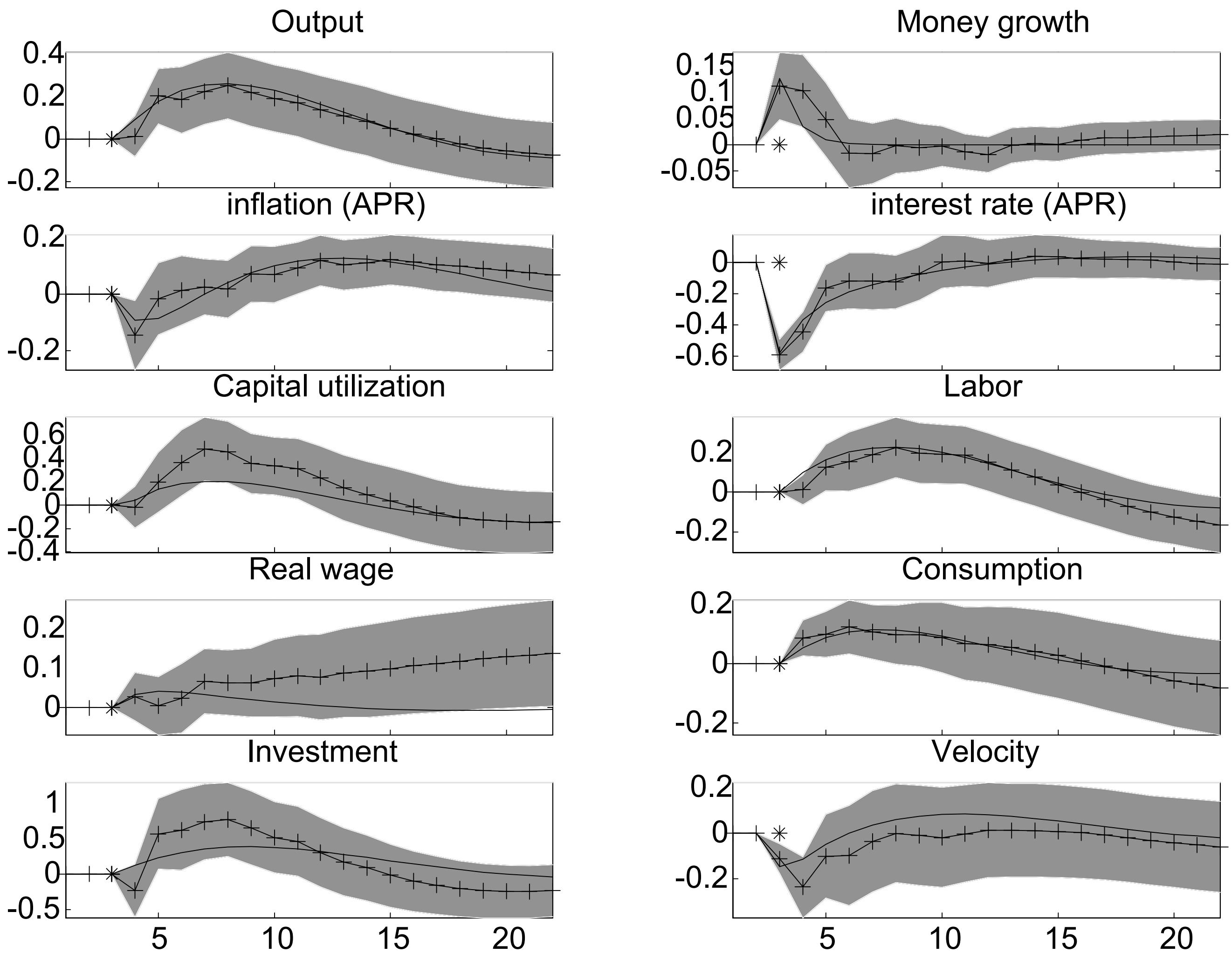
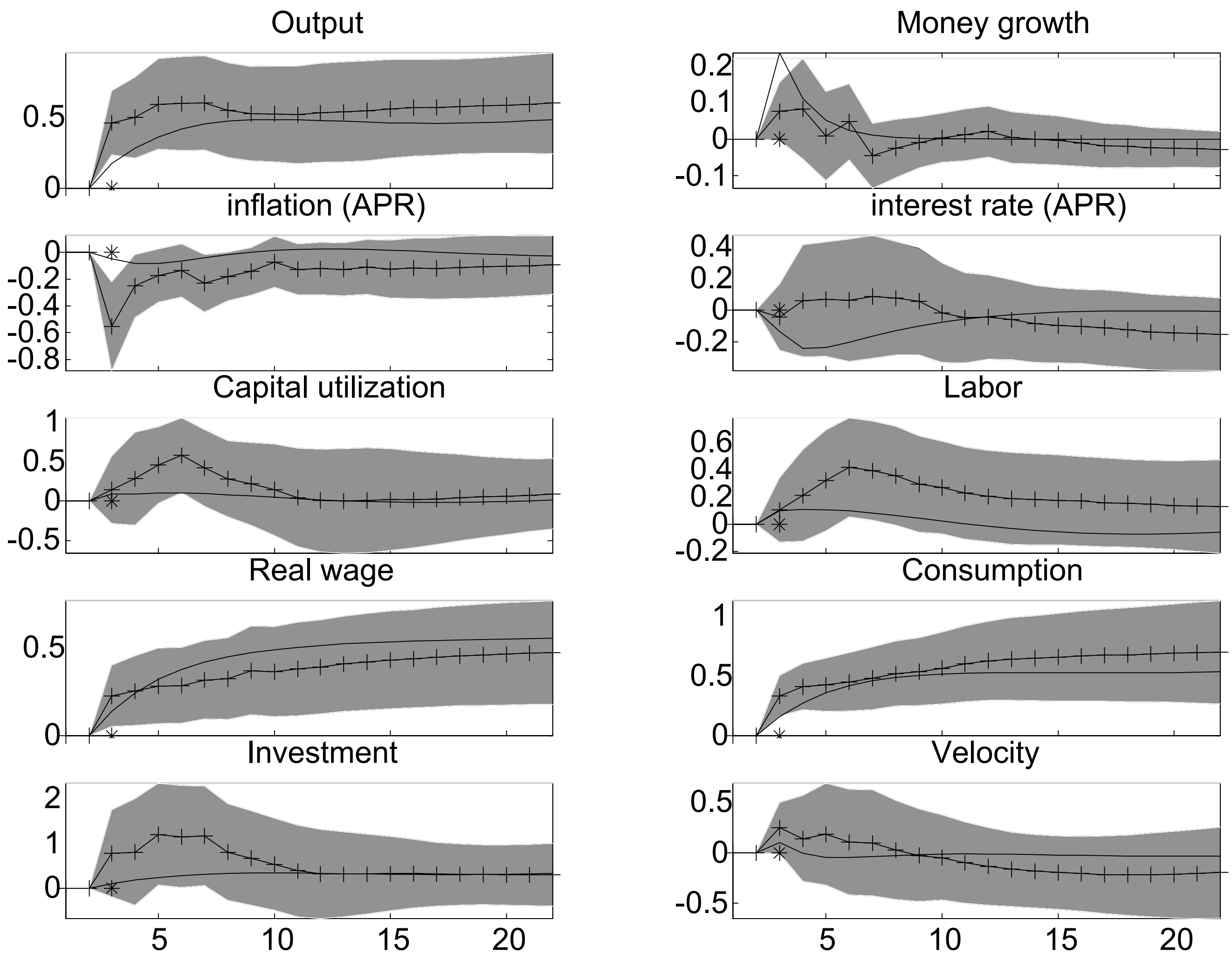


Figure 15: Properties of Model Fit to Policy Impulse Responses Only

Figure 2: Model and Data Impulse Response Functions to a Non-stationary Technology Shock



4.3. Estimation Based on Technology Shocks Alone

We now turn to the results based on estimating the model on technology shocks alone. These results are quite different from our benchmark findings. Table 2 reports the new parameter values. Stickiness in prices has been almost completely eliminated, while the degree of stickiness in wages has moved to its upper bound of 0.99. Adjustment costs in investment and the degree of market power of intermediate good producers have increased substantially.[25] According to Table 3, the standard deviation of the technology shock was cut in half, and the response of money to technology was increased from about 2 to about 3.

Figures 16 and 17 indicate what the consequences of these new parameter values are. Figure 17 shows that the new parameters correct the main failures of the benchmark model in reproducing the dynamic responses to technology. However, these improvements come at great cost in terms of being able to fit the dynamic response to a monetary policy shock. The effect of the shock on inflation in the first 20 quarters is now completely dominated by cut in the interest rate. With the fall in prices and the rise in nominal demand, labor, capital utilization, consumption, investment and output surge. In the case of output and labor, the increase is far too great. The enormous stickiness in the nominal wage rate relative to intermediate good prices implies that the real wage stays low.

In a later draft we will more fully diagnose the implications of these model results. For now, we note that these results confirm the conclusion of the previous subsection: the benchmark results are principally driven by the empirical responses to monetary policy. It is interesting that the monetary policy shock, which has so little impact on the dynamics of the data, plays such an important role in pinning down model parameters.

[25]Standard errors have not yet been computed for these parameter values.

Figure 16: Properties of Model Fit to Technology Impulse Responses Only

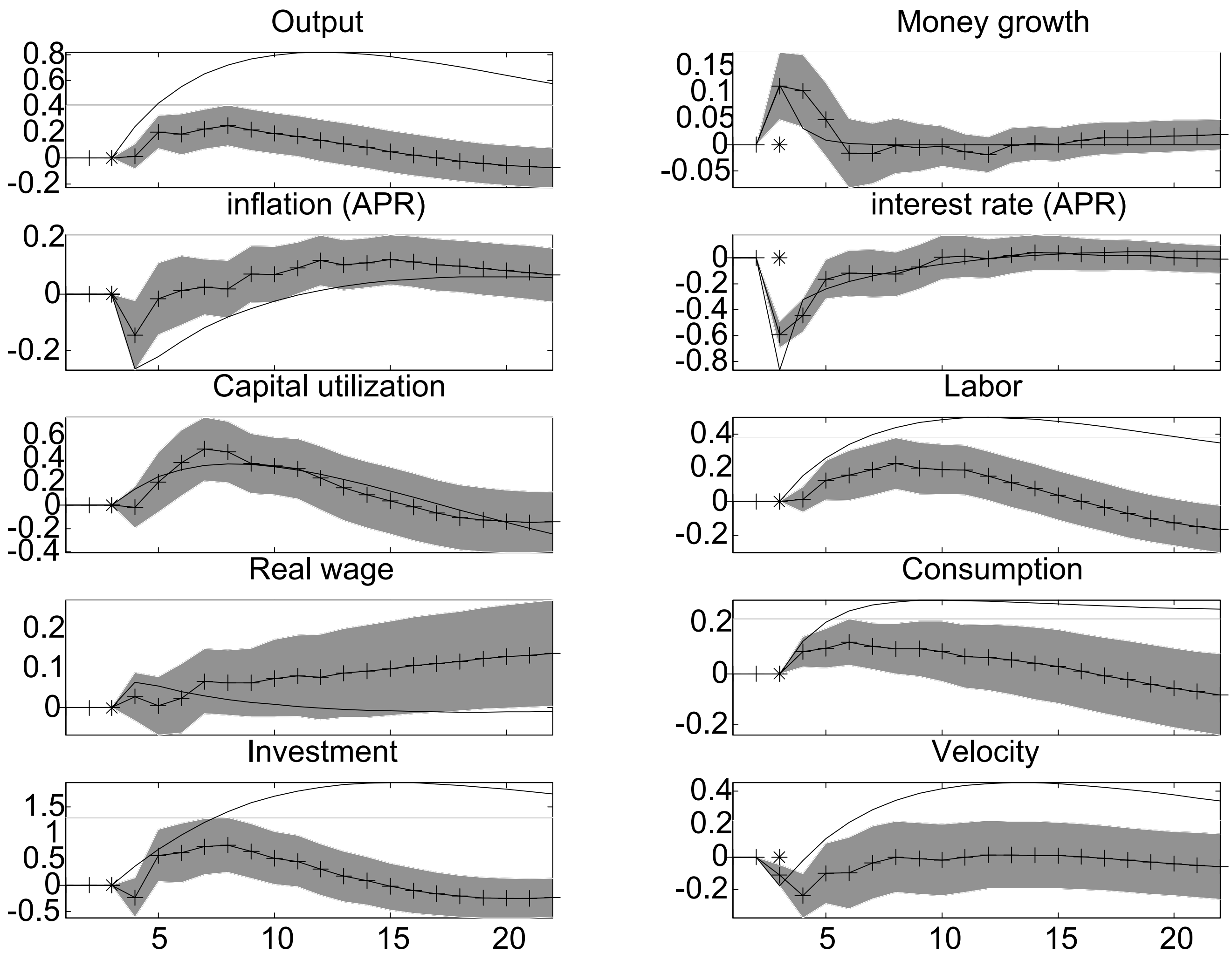
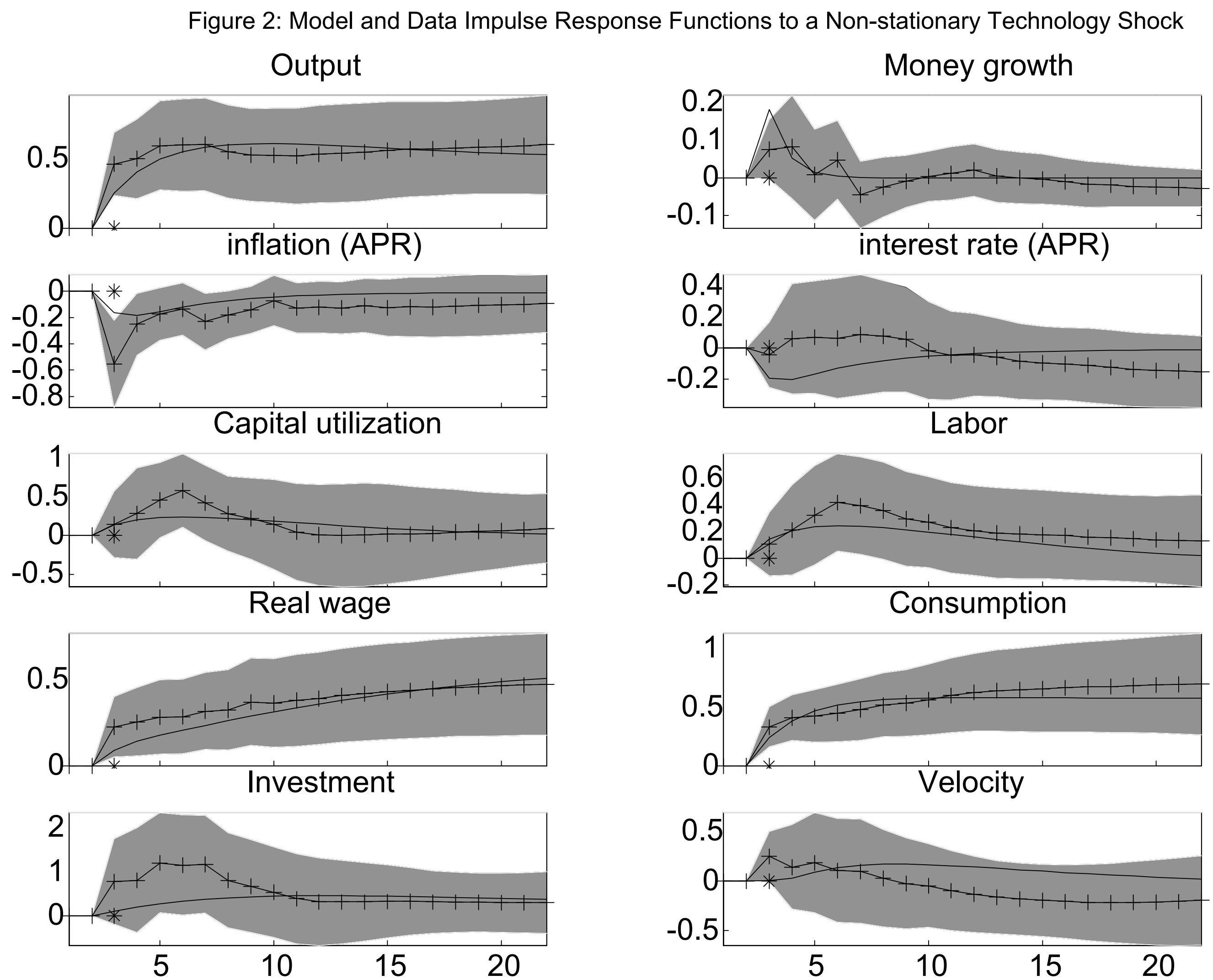


Figure 17: Properties of Model Fit to Technology Impulse Responses Only



5. Conclusion

[to be added later]

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