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Fundamental Economic Shocks and the Macroeconomy

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Abstract

This paper asks how macroeconomic and financial variables respond to economic impulses. We identify structural economic shocks using a strategy that utilizes measures of economic shocks explicitly derived from economic models. We use this approach to identify technology shocks, marginal-rate-of-substitution (labor supply) shocks, and monetary policy shocks in the context of a Factor Augmented VAR similar to that developed by Bernanke, Boivin, and Eliasz (2005). We then examine the Bayesian posterior distribution for the responses of a large number of endogenous macroeconomic and financial variables to these three shocks. These shocks account for the preponderance of output, productivity and price fluctuations. We find that technology shocks have a permanent impact on measures of economic activity, even though this characteristic of technology shocks is not imposed as an identifying restriction. In contrast, the other shocks have a more transitory impact. Labor inputs have little initial response to technology shocks; the response builds steadily over the five year period. Consumption has a sluggish response to the technology shock, consistent with a model of habit formation. Monetary policy has a small response to technology shocks, but "leans against the wind" in response to the more cyclical labor supply shock. This shock has the biggest impact on interest rates. Stock prices respond to all three shocks. A number of other empirical implications of our approach are discussed.

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1. Introduction

This paper investigates how macroeconomic and financial variables respond to structural economic shocks. We use a relatively new and unexplored identification strategy that simultaneously identifies multiple impulses. Our strategy is linked to economic theory without being tied rigidly to a particular theoretical model. Furthermore, it minimizes dependence on arbitrary choices, such as the choice of variables to be included in a vector autoregression (VAR).

Current methods for identifying and estimating economic shocks have been well-studied since Sims's (1980) important contribution. See Stock and Watson (2001) and Christiano, Eichenbaum, and Evans (1999) for recent surveys. A stalwart identification method is to place zero restrictions on a matrix of contemporaneous impact multipliers in a VAR. Although much has been learned through these methods, such zero restrictions rarely conform precisely to the equilibrium decision rules of any dynamic stochastic general equilibrium model (DSGE), a point made by Lucas and Stokey (1987) in response to Litterman and Weiss (1985). Long-run restrictions are more likely to be compatible with a set of DSGE models, although subtle changes in model trending details can make these implications fragile, as King and Watson (1997) have discussed relative to Lucas's theory of the natural rate (1972). Furthermore, economic shocks are often identified one at a time, ignoring potential correlations across shocks.

We propose an identification strategy that is more closely motivated by the insights of economic theory without imposing all the restrictions of a particular economic model. Furthermore, we seek to identify multiple shocks simultaneously, imposing orthogonality across these shocks.[1] Our approach is to use measures of fundamental shocks that are derived from economic models developed in antecedent literature. We call these"model-based measures". In particular, we measure technology shocks as Solow residuals and monetary policy shocks from a Taylor rule specification. In addition, we construct a measure of shocks to the marginal rate of substitution (MRS) between consumption and leisure using a procedure similar to Hall (1997). As Hall notes, these shocks can be interpreted as labor supply shocks.

These measures are potentially noisy. Specifically, since they are mutually correlated it is problematic for our purposes to treat these as clean measures of the true underlying structural impulses. Instead, we follow the structural VAR (SVAR) literature in assuming that all structural shocks are mutually orthogonal. We use our model-based shock measures

[1]Important recent papers in the literature that identify multiple structural shocks include Gali (1992), Leeper, Sims, and Zha (1996), and Del Negro, Shorfheide, Smets, and Wouters (2005).

to derive the linear combination of VAR innovations that best replicates each structural impulse. This allows us to compute identified impulse response functions, and relate the evidence to important macroeconomic questions and alternative models.

In using shock measures derived from economic models, our identification strategy exploits the restrictions implied by economic theory more directly than the typical identifying strategies used in VAR analysis. However, we do not impose all of the restrictions implied by these economic models. (For example, we leave the dynamics unrestricted.) In this sense, our approach is midway between the standard SVAR approach and a fully-articulated DSGE model. Our approach does require strong assumptions, and we do not assert that it pointwise dominates other approaches. Nonetheless, it is a plausible approach that differs from others currently in use, so it could offer a different perspective on economic issues of interest.[2]

Evans and Marshall (2003) used a variant of this method to examine a variety of term structure responses. This paper advances that work along a number of dimensions. First, we use an alternative, and arguably more robust, set of identifying restrictions. Second, rather than restricting our information set to a small number of macroeconomic variables, we incorporate a much larger data set by using the Factor Augmented VAR (FAVAR) approach of Bernanke, Boivin, and Eliasz (2005). This approach allows us to incorporate enough information in the VAR residuals to span the true shocks without exhausting our degrees of freedom. In addition, the approach limits the effect of arbitrary choices regarding which variables to include in the SVAR. Finally, we move from Evans and Marshall's (2003) focus on interest rate responses to examine the responses of a wide range of macroeconomic and financial data. This enables us to explore a number of substantive questions that clearly can benefit from a multi-shock context.

Specific questions we address include the following:

- Can a small number of shocks account for most output fluctuation?

- How realistic is the traditional focus on technology shocks as drivers of business cycle variation in output, investment, and labor inputs? (Kydland and Prescott, 1982, and subsequent RBC literature)

- Is it reasonable to associate technology shocks with permanent shocks to output (Blanchard and Quah, 1989; Gali, 1992) or to labor productivity (Gali, 1999; Christiano,

[2]In linking identification to the insights of economic theory without tying the identification too tightly to any single economic model, our approach is related to Del Negro, Shorfheide, Smets, and Wouters (2005). They use a Bayesian approach to identify a VAR in which the prior distribution is derived from a particular dynamic general equilibrium model. The strength of the prior determines how tightly the identification is linked to the underlying model.

Eichenbaum, and Vigfuson, 2003), with other shocks (such as "aggregate demand" shocks) having only transient effects on these variables?

- What drives procyclical labor productivity: technology shocks or demand shocks ("labor hoarding")?

- Are technology shocks contractionary for labor hours and employment (as argued by Basu, Fernald, and Kimball, 2004, and Gali, 1999), or do these measures of labor inputs rise contemporaneously with an expansionary technology shock (as argued by Christiano, Eichenbaum, and Vigfuson, 2003)?

- What is the role of monetary policy in aggregate fluctuations? Is monetary policy driven largely by responses to economic conditions, or is there an important role for exogenous monetary policy shocks? Does monetary policy respond differently to technology ("supply") shocks than to labor supply ("demand") shocks? Are monetary policy shocks an important source of business cycle variation (as implied by the estimates of Strongin, 1995) or are they rather minor contributors (as discussed by Sims and Zha, 1998, and Christiano, Eichenbaum, and Evans, 1999)?

- What drives fluctuations in the price level and inflation? In particular, what is the role of real side impulses (such as Phillips curve effects or shocks to marginal costs)?

- Are movements in asset prices driven to a significant extent by macroeconomic impulses? Or are asset prices primarily driven by dynamics internal to the financial markets that are largely orthogonal to the macroeconomy? If macro impulses have a significant role in financial markets, which specific impulses are most important?

Our results shed light on these questions. We find that the three shocks we identify account for around 72% of the short-run variation in output and over 84% of the variation in output at longer horizons. In addition, these shocks account for more than 50% of the long-run variation in inflation, although they account for only about 20% of inflation variation at the 3-month horizon. The MRS shock is an important driver of short-run output variation, but the effect of the technology shock is much longer-lived. Thus, our evidence favors the permanent vs. transitory distinction between technology shocks and other shocks, even though we do not impose this distinction as an identifying restriction. We find that the procyclical response of labor productivity is due almost entirely to procyclical technology shocks. Labor input measures display almost no contemporary response to technology shocks, but rise gradually in the years following the shock. Similarly, wages have only a small initial response to technology shocks, even though the technology shocks boost labor's marginal product. Wages then rise monotonically over the next four years.

Monetary policy shocks have a very small impact on real economic activity. While these shocks do account for a good deal of the short-run variation in the fed funds rate, their impact is extremely short-lived. Longer-lived policy actions are mostly endogenous responses of the Fed to other shocks. In particular, the Fed displays a rather small response to technology shocks, but strongly "leans against the wind" in response to the more cyclical MRS shock. Finally, while most variation in stock prices is accounted for by sources other than our three identified shocks, there are a number of intriguing patterns that point to linkages between financial markets and the macroeconomy. In particular: the MRS shock accounts for most variation in Treasury yields, and all three shocks have significant impacts on stock prices.

The paper is organized as follows. Section 2 describes the basic framework we use. Section 3 discusses our Bayesian approach to statistical inference. Section 4 describes the construction of our three model-based shock measures and discusses our FAVAR specification. Section 5 describes our empirical results, and section 6 concludes.

2. Identifying a Structural VAR using Model-Based Shock Measures

2.1. Basic Framework

We study the responses of macroeconomic and financial variables to a set of m fundamental shocks. Let ε_t denote the $m \times 1$ vector of shocks we wish to identify. It is assumed that ε_t is serially uncorrelated, with $E\varepsilon_t = 0$ and

$$E\varepsilon_t\varepsilon_t' = I \tag{2.1}$$

A key assumption in our approach is that the econometrician observes a $m \times 1$ vector η_t of model-based measures of these processes. For example, if one element of the ε_t vector is an exogenous technology shock, the corresponding observable model-based measure might be a data series consisting of Solow residuals. Or, if another element of ε_t were a monetary policy shock, the corresponding model-based measure might be the residual from an empirical Taylor rule. These model-based measures may be serially correlated and contaminated with measurement error. Furthermore, they may not be clean, in the sense that a given element of η_t may be a function of all of the ε_t's. For example, the measured Solow residual series may be contaminated with monetary policy shocks, as argued by Evans (1992). To capture these possibilities, we assume that the η_t vector of model-based shocks is related to the true, unobserved shock vector process ε_t by

$$\eta_t = D_0\varepsilon_t + D_1\varepsilon_{t-1} + ... + D_K\varepsilon_{t-K} + \ w_t \tag{2.2}$$

where $D_k, k = 0, ..., K$, are $m \times m$ matrices of parameters and w_t is an $m \times 1$ vector of random measurement errors with covariance matrix Σ_w for which

$$E\varepsilon_t w_{t-j} = 0, \forall j = 0, \pm 1, \pm 2, ... \tag{2.3}$$

We assume that D_0 is nonsingular. If D_0 is diagonal, then the innovation to a given model-based shock $\eta_{i,t}$ is a function only of its own fundamental shock $\varepsilon_{i,t}$ (plus the measurement error w_t). However, if the i^{th} row of D_0 is non-diagonal, then the innovation to the shock $\eta_{i,t}$ is a function of two or more elements of ε_t.

In addition to the η_t vector, the econometrician also observes an $n \times 1$ vector Y_t of economic variables, where $n \geq m$. The law of motion for Y_t has the following structural representation:

$$AY_t = \widehat{B}(L)Y_{t-1} + \begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix} \tag{2.4}$$

where A is an $n \times n$ nonsingular matrix of parameters, $\widehat{B}(L)$ is an $n \times n$ matrix of polynomials in the lag operator, and γ_t is an $(n-m) \times 1$ vector of additional i.i.d. structural shocks orthogonal to ε_t. In particular,

$$E\left[\begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix} \begin{pmatrix} \varepsilon_t' \ \gamma_t' \end{pmatrix}\right] = I \tag{2.5}$$

In the general case, representation (2.4) could be the reduced form of some linearized or log-linearized DSGE model. Alternatively, it could be an atheoretic forecasting model. From the standpoint of our investigation, γ_t are "nuisance shocks" that we do not seek to identify. Equation (2.4) can be written as a VAR:

$$Y_t = B(L)Y_{t-1} + u_t \tag{2.6}$$

where u_t is an $n \times 1$ vector of VAR residuals with covariance matrix Σ_u,

$$B\left(L\right) = A^{-1}\widehat{B}(L)$$

and

$$\begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix} = Au_t \tag{2.7}$$

It is convenient to partition the rows of A as follows:

$$A = \begin{bmatrix} A_\varepsilon \\ A_\gamma \end{bmatrix}$$

where the $m \times n$ matrix A_ε consists of the first m rows of A. Notice that

$$\varepsilon_t = A_\varepsilon u_t. \tag{2.8}$$

According to equation (2.8), we can recover the structural shocks ε_t from the VAR residuals if we can identify the mn elements of the matrix A_ε. To that end, note that we can combine equations (2.2) and (2.8) to get

$$\eta_t = C_0 u_t + C_1 u_{t-1} + ... + C_K u_{t-K} + w_t \tag{2.9}$$

where the $n \times m$ matrices C_k, $k = 0, ..., K$, are defined by

$$C_k \equiv D_k A_\varepsilon, k = 1, ..., K. \tag{2.10}$$

Equation (2.10) with $k = 0$ means that matrix A_ε is identified if we can identify the matrices C_0 and D_0. In the next subsection we turn to this task.

2.2. Identification of A_ε

First, note that equations (2.1) and (2.8) imply that

$$I = A_\varepsilon \Sigma_u A_\varepsilon'. \tag{2.11}$$

Equations (2.10) and (2.11) in turn imply

$$D_0 D_0' = C_0 \Sigma_u C_0' \tag{2.12}$$

which says that D_0 is a decomposition of $C_0 \Sigma_u C_0'$. To identify D_0 from data, we first impose restrictions sufficient to ensure that $C_0 \Sigma_u C_0'$ can be estimated from the data. We then impose additional assumptions to ensure that the decomposition in equation (2.12) is unique.

Let us turn first to the estimation of $C_0 \Sigma_u C_0'$. Matrix Σ_u can be estimated in the usual way from the variance-covariance matrix of the VAR residuals. Estimation of C_0 requires an additional assumption:

$$E\gamma_t w_t = 0 \tag{2.13}$$

Together, equations (2.3), (2.7), and (2.13) ensure that $E u_t w_t' = 0$, so we can estimate $C_k, k = 0, ..., K$ by regressing η_t on u_t.[3]

[3] OLS estimation of equation (2.9) is consistent, but not efficient. However, using OLS estimation simplifies computation of the Bayesian posterior distribution of the model parameters, which we use for inference. See the appendix for details.

While equation (2.13) is a strong restriction, some form of strong exclusion restrictions must be imposed in virtually any procedure that seeks to identify a small number of shocks using a large data set. For example, index model approaches, such as Sargent and Sims (1977) or Stock and Watson (1989), are typically implemented by strongly restricting the covariances among fundamental shocks and measurement disturbances.

Given the estimates of C_0 and Σ_u, equation (2.12) represents $m(m+1)/2$ restrictions on the m^2 elements of D_0. We can identify D_0 if we impose another $m(m-1)/2$ restrictions on D_0. It is useful to formalize these restrictions by specifying $m(m-1)/2$ free parameters, $\tilde{d}$, along with a mapping $d : R^{m^2} \rightarrow R^{m(m-1)/2}$ such that, given $\left\{\tilde{d}, C_0, \Sigma_u\right\}$, D_0 is the solution to the following system of n^2 equations:

$$\begin{aligned} d\left(D_0\right) &= \tilde{d} \\ D_0 D_0' &= C_0 \Sigma_u C_0' \end{aligned} \tag{2.14}$$

For example, one possible set of identifying restrictions could be to require that D_0 be lower-triangular.[4] These restrictions would be represented in system (2.14) by having the mapping $d(\cdot)$ pick out the $m(m-1)/2$ upper triangular elements of D_0, and then setting $\tilde{d}$ equal to a vector of zeros. (In section 4.2, below, we discuss the specification of $d(\cdot)$ and $\tilde{d}$ that we actually use in the empirical part of this paper.) Having estimated C_0 and identified D_0, we can then identify A_ε using equation (2.10), which implies that $A_\varepsilon = D_0^{-1} C_0$. The structural shock vector ε_t can then be identified using equation (2.8).

To compute impulse responses of Y_t to ε_t, rewrite the reduced form (2.6) as

$$Y_t = B(L) Y_{t-1} + A^{-1} \begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix}. \tag{2.15}$$

Computing impulse responses to ε_t requires that we know the first m columns of A^{-1}, which we can denote "$[A^{-1}]_\varepsilon$". This submatrix can be computed from knowledge of A_ε using the relation

$$\left[A^{-1}\right]_\varepsilon = \Sigma_u A_\varepsilon' \tag{2.16}$$

which follows directly from equation (2.11).

Once $[A^{-1}]_\varepsilon$ is identified, we can compute the response of any variable z_t, even one not included in the vector Y_t. To do so, we augment system (2.6) and (2.7) with another equation in z_t:

$$\begin{bmatrix} Y_t \\ z_t \end{bmatrix} = \begin{bmatrix} B(L) & \mathbf{0} \\ \phi(L) & \theta(L) \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} A^{-1} & 0 \\ F & G \end{bmatrix} \left[\begin{array}{c} \begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix} \\ \nu_t \end{array} \right]. \tag{2.17}$$

[4] Evans and Marshall (2003) pursue this strategy after rejecting the testable hypothesis that D is diagonal.

In equation (2.17), $\phi(L)$ and $\theta(L)$ are respectively $1 \times n$ and 1×1 vector polynomials in the lag operator, F and G are $1 \times n$ and 1×1 parameter vectors, and ν_t is a serially uncorrelated disturbance that is also uncorrelated with ε_t and γ_t. The zero restrictions in equation (2.17) ensure that, given knowledge of Y_{t-1} and its lags along with ε_t and γ_t, neither ν_t, z_t, nor its lags are needed to determine Y_t.

2.3. Expanding the Information Set

As with any structural VAR, a key requirement of our approach is that the true fundamental shocks ε_t are spanned by the VAR residuals u_t. To ensure that this is indeed the case, one would want to incorporate a large number of data series in the VAR. However, to do so directly would quickly lead to degrees-of-freedom problems. As discussed in Bernanke, Boivin, and Eliasz (2005), VARs typically used in the literature incorporate no more than 6 to 8 variables.[5]

To address this problem, we follow Bernanke Boivin, and Eliasz (2005) and implement equation (2.4) as a Factor Augmented Vector Autoregression (FAVAR). Specifically, we use a set X_t of p observable data series (where p is large), and we assume that X_t is a function of n factors $\widehat{Y}_t$, where n is much smaller than p:

$$X_t = \Lambda \widehat{Y}_t + e_t. \tag{2.18}$$

We assume that e_t displays weak cross-correlation in the sense of Stock and Watson (1998). As in Stock and Watson (1998, 2002) and Bernanke Boivin, and Eliasz (2005), we estimate $\widehat{Y}_t$ as the first n principal components of X_t. We then use $\widehat{Y}_t$ in equation (2.4) in place of Y_t.

Note that this is a two-step procedure: first we estimate equation (2.18) to generate $\widehat{Y}_t$, and then we estimate equation (2.4) and impose the strategy of section 2.2 to identify the shocks ε_t. In using this two-step approach we follow Stock and Watson (1998, 2002). In principle, one could combine these two steps. However, Bernanke Boivin, and Eliasz (2005) argue that the gains from doing so appear to be rather small, while the computational burden increases substantially.[6]

[5] These degrees-of-freedom problems can be mitigated to some extent by imposing a Bayesian prior. For example, Leeper, Sims and Zha (1996) use this approach to estimate a VAR with 18 variables.

[6] There is a technical issue in using $\widehat{Y}_t$ in place of Y_t in equation (2.17): if z_t is one of the elements of the information vector X_t, then it is not clear that the zero restrictions in equation (2.17) will hold. In their treatment of dynamic factor models, Stock and Watson (2005) test a variety of restrictions of this form. While they often reject the zero restrictions in a statistical sense, they find that the deviations from the zero restrictions are of no economic significance in virtually all cases. We will continue to impose the zero restrictions in equation (2.17) as a maintained assumption

3. Bayesian Inference

Given the $\widehat{Y}_t$ series estimated in the first step, the remaining parameters to be determined in the second step are $\left\{B, \Sigma_u, C, \Sigma_w, \tilde{d}\right\}$, where B contains the coefficients of the lag polynomial $B(L)$, $C \equiv \{C_k\}_{k=0}^{K}$, and $\tilde{d}$ is the vector of free parameters that identifies the elements of matrix D_0 in equation (2.14). A joint prior distribution can be imposed on these parameters, and the posterior distribution can then be computed. In doing so, we are explicitly treating the generated series $\widehat{Y}_t$ as known data. [7]

Note that the parameter vector $\tilde{d}$ differs from the other parameters. Since $m(m-1)/2$ restrictions have been imposed on the D_0 matrix, the model is exactly identified. Therefore, the parameters $\{B, \Sigma_u, C, \Sigma_w\}$ exhaust the information in the data, so any specification of the $m(m-1)/2$ elements of $\tilde{d}$ is equally likely. Thus the prior on $\tilde{d}$ equals the posterior, so this prior acts as a way of specifying soft restrictions on the D_0 matrix.

The appendix contains a detailed description of how one computes the posterior distribution for $\{B, \Sigma_u, C, \Sigma_w\}$ given an uninformative prior on these four parameter elements. This paper only explores the implications of this uninformative prior. It is straightforward to amend this procedure for an informative prior.

4. Empirical Implementation

4.1. Model-Based Shock Measures

In our empirical application of the identifying strategy of section 2, we seek to identify three shocks: a technology shock, a marginal-rate-of-substitution shock that can be interpreted as a labor supply shock, and a monetary policy shock. To implement the model-based identification strategy, we need model-based measures of these three shocks. In this section we describe how we construct these measures.

4.1.1. Technology Shocks

Since Prescott (1986), the driving process for aggregate technology shocks in real business cycle models has been calibrated to empirical measures of Solow residuals. A large literature, including Prescott (1986), has noted that a portion of the fluctuations in standard Solow

[7] Note, in addition, we are treating the model-based measures η_t as known, even though, in some cases, these measures may involve estimated parameters.

An alternative procedure would be to impose a prior on parameter matrices $\{\Lambda, \Sigma_\nu\}$ in equation (2.18), and then compute the joint posterior over all the parameters. However, these matrices are extremely large. In our empirical application, Λ is 190×6 and Σ_ν, the covariance matrix of ν_t, is 190×190. As a result, this alternative procedure borders on the infeasible.

residual measures is endogenous, responding to macro shocks.[8] Basu, Fernald, and Shapiro (2001b) provide a recent estimate of technology innovations that attempts to reduce these influences. Ignoring industry composition effects, their aggregate analysis specifies production as follows:

$$Y_t = z_t \ g_t F(v_t K_t, e_t N_t)$$

$$\ln z_t = \mu + \ln z_{t-1} + \eta_{Tech,t} \tag{4.1}$$

where Y, z, v, K, e, and N are the levels of output, technology, capital utilization rate, capital stock, labor effort, and labor hours.[9] The object g_t represents costs of adjusting employment and the capital stock. It is an explicit function of observable data, and is calibrated from econometric estimates in the literature (see Shapiro (1986) and Basu, Fernald, and Shapiro (2001a,b)). F is a production function that is homogeneous of degree $\zeta \geq 1$, allowing for the possibility of increasing returns. Basu, Fernald, and Shapiro (2001a,b)) specify an economic environment where the unobserved variables v and e can be measured as proportional to the workweek of labor and capital. Assuming $\zeta = 1$ — constant-returns-to-scale — Basu, Fernald, and Shapiro (2001b) use time-varying cost shares to compute a quarterly, aggregate measure of the technology innovation, $\eta_{Tech,t}$.

We use Basu, Fernald, and Shapiro's (2001b) quarterly, aggregate measure of technology for our model-based empirical measure η_{Tech} of the aggregate technology shock.[10] Although this quarterly measure includes controls for many latent, endogenous features, data limitations prevent controlling for industry compositional effects. This potentially introduces measurement error into this series. The data begin in 1965:II and end in 2000:IV.

4.1.2. Marginal-Rate-Of-Substitution Shocks

A shock to the marginal rate of substitution (MRS) between consumption and leisure can potentially shift aggregate demand for goods and services. Hall (1997), Shapiro and Watson (1988), and Baxter and King (1990) find substantial business cycle effects from empirical measures of intratemporal marginal rates of substitution between consumption and leisure. To generate a model-based empirical measure of an MRS shock, we generalize Hall's (1997) procedure to allow for time-nonseparable preferences.[11] Consider a representative consumer with the following utility specification:

$$U(C_t, N_t) = \xi_t \frac{\left(C_t - b\overline{C}_{t-1}\right)^{1-\gamma}}{1-\gamma} - \frac{N_t^{1+\phi}}{1+\phi}$$

[8] For example, see Burnside, Eichenbaum and Rebelo (1993) and Braun and Evans (1998).

[9] Throughout this paper, we omit the time subscript t if no ambiguity is implied.

[10] We thank John Fernald for providing us with this time series on technology shocks.

[11] Holland and Scott (1998) study a similar MRS shock for the United Kingdom economy.

$$\ln \xi_t = \rho(L) \ln \xi_{t-1} + \eta_{MRS,t} \tag{4.2}$$

where C is the consumption by the representative agent, $\overline{C}$ represents the per-capita aggregate consumption level, N is labor hours, ξ is a serially correlated preference shifter, and η_{MRS} is a serially independent shock. The first-order conditions for consumption and labor hours lead to the following intratemporal Euler equation (or MRS relationship)

$$\frac{\xi_t \left(C_t - b\overline{C}_{t-1}\right)^{-\gamma}}{N_t^{\phi}} = \frac{1}{W_t \left(1 - \tau_t\right)} \tag{4.3}$$

where W_t is the real wage and τ_t is the labor tax rate. Taking logs, we obtain

$$ln\ \xi_t = \phi\ ln\ N_t - lnW_t - \ln\left(1 - \tau_t\right) + \gamma ln \left[C_t - b\overline{C}_{t-1}\right]. \tag{4.4}$$

In equilibrium, the per-capita aggregate consumption equals the consumption levels of the representative agent, so $\overline{C} = C$.

We use equation (4.4) to obtain an empirical measure of $\ln \xi_t$. We then compute our model-based empirical measure $\eta_{MRS,t}$ of the MRS shock as the residual from the OLS estimate of equation (4.2). Our data are quarterly and extend from 1964:I to 2000:IV. Consumption is measured by per capita nondurables and services expenditures in chain-weighted 1996 dollars. Labor hours correspond to hours worked in the business sector per capita. The real wage corresponds to nominal compensation per labor hour worked in the business sector deflated by the personal consumption expenditure chain price index. The hours and compensation data are reported in the BLS productivity release. Finally, our measure of the labor tax rate is a quarterly interpolation of the annual labor tax series used in Mulligan (2002).[12] We calibrate the utility function parameters as follows. First, to ensure balanced growth we set $\gamma = 1$, corresponding to log utility for consumption services. Second, we use Hall's (1997) value for $\phi = 1.7$, corresponding to a compensated elasticity of labor supply of 0.6. Finally, we set the habit persistence parameter $b = 0.73$ as estimated by Boldrin, Christiano and Fisher (2001).

We measure η_{MRS} as the residual in equation (4.2). We estimate a sixth-order polynomial for $\rho(L)$. In addition, the MRS measure ξ exhibits noticeable low frequency variation, so we also include a linear time trend in the regression to account for demographic factors that are beyond the scope of this analysis. If the theoretical variables and data series coincide and our estimate of $\rho(L)$ is correct, then our measure of η_{MRS} would equal ε_{MRS}. If, however, our measures of consumption, labor hours, and the spot real wage differ from the theory, then η_{MRS} would represent a noisy measure of ε_{MRS}. In order to allow for serially-correlated

[12] We would like to thank Casey Mulligan for providing us with his labor tax rate data.

measurement errors in ξ_t, we use an instrumental variables estimator to estimate $\rho(L)$.[13]

If our model-based measure η_{MRS} were a clean measure of the true structural shock ε_{MRS}, it should be causally prior to any endogenous variables. While we do not use the model-based measure directly as the structural shock, clearly causal priority is a desirable characteristic for our η_{MRS} measure. Gali, Gertler, and Lopez-Salido (2001) specifically raise this issue with regard to a series similar to our η_{MRS} measure, questioning whether it was Granger-causally prior to output, the short-term interest rate, and the term spread. When we replicate the Gali, Gertler, and Lopez-Salido (2001) causality tests for our η_{MRS} measure, we find no evidence that η_{MRS} is Granger-caused by the variables they consider (detrended GDP, the federal funds rate, and the term spread). Details of these causality tests are displayed in Table 1.

Derived this way, our MRS shock has a clear interpretation as a preference shifter. However, macroeconomic researchers have offered several alternative interpretations for the random marginal rate of substitution shifter ξ_t in equation (4.3).[14] First, the home production literature due to Benhabib, Rogerson, and Wright (1991), Greenwood and Hercowitz (1991), and Chang and Shorfheide (2003), among others, suggests that ξ_t could be a productivity shock to the production of home goods. Second, inertial wage and price contracts will distort the simple intratemporal Euler equation as it is specified in (4.3). In particular, in the Calvo pricing environments considered by Christiano, Eichenbaum, and Evans (2005) and Galí, Gertler, Lopez-Salido (2001), alternative versions of (4.3) hold. Third, Mulligan (2002) interprets ξ_t as reflecting labor market distortions, such as changes in tax rates or union bargaining power. To the extent that these alternative explanations have different theoretical implications for impulse response functions, an empirical analysis of our MRS shock can help shed light on which explanation seems to be consistent with the aggregate data.

4.1.3. Monetary Policy Shocks

Unlike the previous two shock measures, there is no well-developed theory that derives monetary policy shocks from an optimizing framework. However, many theoretical models assume that the monetary authority sets monetary policy via some variant of a Taylor (1993) rule. That is, the short-term interest rate is set as an increasing function of both inflation and the output gap (a measure of the shortfall in economic activity compared to its

[13] Our shock identification strategy assumes that the measurement errors in our model-based shocks are independent of the VAR innovations. Consequently, we use real GDP, the GDP price index, and commodity prices as instruments.

[14] As Hall (1997) pointed out, the greatest amount of evidence against Eichenbaum, Hansen, and Singleton's (1988) preference specifications surrounded the intratemporal Euler equation for consumption and leisure.

potential). In some specifications, lags of the short-term interest rate are included in order to capture the desire of the monetary authority to smooth changes in the interest rate.[15] In these models, the natural specification for monetary policy shocks is the disturbance to the short-term interest rate that is orthogonal to these systematic components of the Taylor Rule. We adopt this approach for our model-based measure of the monetary policy shock η_{MP}.

The particular approach we use is to specify a backward-looking Taylor rule, so the interest rate is a function of current and lagged inflation, as opposed to expected future inflation. In addition, the output gap is not observed, so some empirical proxy for this gap variable must be used. In the spirit of taking our model-based measures from approaches proposed in antecedent literature, we use a gap measure derived from work by Staiger, Stock, and Watson (1997). In particular, we measure the gap as the difference between the current unemployment rate and the Staiger-Stock-Watson measure of the natural rate of unemployment.[16] In addition, we allow the coefficients on inflation and on the gap variable to be regime dependent. Specifically, we allow for three regimes: before 1979:Q4, 1979:Q4 - 1982:Q4, and after 1982:Q4. The specific model is as follows:

$$rff_t = \sum_{j=1}^{4} \alpha_j rff_{t-j} + \sum_{k=1}^{3} \left[\beta_k \left(I_k ugap_t\right) + \delta_k \left(I_k \pi_t\right)\right] + \eta_{MP,t} \tag{4.5}$$

where rff_t denotes the fed funds rate, $ugap_t$ denotes the gap between current unemployment and the Staiger-Stock-Watson measure of the natural unemployment rate,[17] π_t denotes the log change in the GDP deflator, and I_k is an indicator variable for the three regimes. The data run from 1959:I through 2000:IV.

4.1.4. Correlations among model-based measures

Table 2 displays the correlations among our three model-based measures $\{\eta_{Tech}, \eta_{MRS}, \eta_{MP}\}$. As can be seen, the correlations are small but non-zero. As a result, we are reluctant to use them as clean measures of the true structural shocks ε_t. Instead, we use them as inputs into the identification strategy described above in section 2.[18] In section 5.8, below, we consider some interpretive problems that would arise if we were to treat the model-based measures as error-free measures of the structural shocks.

[15] A time-varying inflation target is also sometimes included. See, e.g., Kozicki and Tinsley (2001).

[16] We have experimented with several other specifications for the Taylor Rule, including measuring the gap as detrended output, and using real-time data. The results are very close to those in our baseline specification, except the error bands are somewhat tighter when we use the Staiger-Stock-Watson gap measure.

[17] We obtained data on $ugap_t$ from Mark Watson's website.

[18] Boivin and Giannoni (2006) develop an alternative approach to handling potential mismeasurement of structural shocks within a fully specified DSGE model.

4.2. Identifying restrictions

To identify the model, we must impose $m(m-1)/2$ restrictions on matrix D_0. Since $m = 3$, we need 3 restrictions. To motivate the restrictions we impose, note that our procedure is only likely to be informative if the model-based measures contain a good deal of information about the shocks they seek to identify. Specifically, a shock measure η_i is informative about ε_i only if most of the variation in η_i, after controlling for measurement error w_t, is accounted for by ε_i. Equations (2.2) and (2.1) imply that

$$var_{t-1}\left(\eta_{i,t} - w_{i,t}\right) = \sum_{j=1}^{m} D_{0,ij}^2 \tag{4.6}$$

where $D_{0,ij} = (i,j)^{th}$ element of matrix D. We will refer to the left-hand side of equation (4.6) as the "non-noise variance" of $\eta_{i,t}$. To ensure that most of this variance is driven by the own shock ε_i, we need the fraction of this variance associated with the diagonal element $D_{0,ii}$ to be fairly large. Our restrictions on D_0 are motivated by this consideration. In particular, we restrict the three diagonal elements such that

$$\frac{D_{0,ii}^{2}}{\sum_{j=1}^{m} D_{0,ij}^{2}} = \tilde{d}_i, \ \ i = 1,2,3 \tag{4.7}$$

where $\tilde{d}_i$ is drawn from a uniform distribution with support [.80, .95]. This ensures that between 80% and 95% of the non-noise variance of each model-based measure η_i is due to its own shock ε_i.[19]

4.3. FAVAR Specification

In order to ensure that our information set X_t in equation (2.18) is big enough to span the space of the shocks ε_t we seek to identify, we use 190 data series in X_t. Thirty-six of these are quarterly data, while 154 are monthly series that have been quarterly averaged. The data sample is from 1967:Q2 through 2000:Q4. The data series used are listed in Table 1A in the Data Appendix, along with the transformations used to induce stationarity.[20] We set $n = 6$, and we compute $\widehat{Y}_t$ in equation (2.18) as the first six principal components of X_t.[21] Four

[19] Restrictions (2.12) and (4.7) constitute a system of nine equations in the nine unknown elements of D_0. However, these equations are nonlinear, so there is no guarantee that a solution to this system exists. In practice, for the estimated matrix $C_0\Sigma_u C_0'$ (or for the draws of this matrix from its postierior distribution), we find no difficulties solving the system as long as $\tilde{d}_i < 0.95$. When $\tilde{d}_i$ is very near unity for $i = 1,2,3$, however, we find that no solution exists. Perhaps this is not surprising, since $\tilde{d}_i = 1$, $\forall i$, cannot be a solution to the system if $C_0\Sigma_u C_0'$ is non-diagonal.

[20] We control for outliers by replacing any data point more than six times the interquartile range (IQR) above the series median with $median + 6 \times IQR$ (and analogously for data points more than $6 \times IQR$ below the IQR). All transformed series are then de-meaned and standardized.

[21] When we increase the number of principal components to eight, the results are almost identical to those when six principal components are used. In no case are the substantive implications changed.

quarterly lags of each principal component are used in the VAR, equation (2.4). We then use equation (2.17) (substituting $\widehat{Y}_t$ for Y_t) to compute the responses to $\{\varepsilon_{TECH}, \varepsilon_{MRS}, \varepsilon_{MP}\}$ of a number macroeconomic and financial market variables, using the approach of Zha (1999).

The model-based measures only provide useful information for identifying A if they are correlated with the VAR residuals u_t. Table 3 provides evidence on these correlations in the data we use. It displays the R^2s for the OLS regressions in system (2.9) using our measures of η_t. These R^2s show that over 50% of the variation in each model-based measure is accounted for by the VAR residuals. In addition, the F-statistics testing the hypotheses that the VAR residuals are uninformative for the η_t measures reject these hypotheses at any desired significance level. Under our identifying restrictions, these statistics imply that our measures are potentially informative for the true structural shock vector ε_t.

5. Empirical Results

The data we use are described in the Data Appendix. Our empirical results are displayed in Table 4 and Figures 1 - 7. For each endogenous variable listed, Table 4 gives the median fraction of 3-, 12-, and 60-month ahead forecast variance accounted for by the three identified shocks, $\{\varepsilon_{MP}, \varepsilon_{MRS}, \varepsilon_{TECH}\}$, according to the posterior distribution. The fourth line in each panel gives the median fraction of each forecast variance accounted for by the three shocks collectively. The two numbers in parentheses following each median statistic give the 95% and 5% quantiles of the posterior distribution for each forecast variance fraction. Figures 1 - 7 display the median impulse responses of selected endogenous variables. The upper and lower dashed lines give the 95% and 5% quantiles of the response distribution, respectively. All of these statistics were computed using 500 draws from the posterior distribution of the model's parameters.

5.1. Long Run Behavior of the Economy

Figure 1 displays the responses of GDP and labor productivity to our three identified shocks over an 80 quarter horizon. There is clear evidence that technology shocks induce permanent shifts in the level of GDP and productivity. In contrast, the responses to the MRS shock and the monetary policy shock appear to display mean reversion, with little evidence of a permanent level shift for GDP or productivity.

An alternative way of describing the posterior distribution of these long run responses is in Table 5, which gives the probability that the 80-quarter ahead response exceeds zero. For the technology shock, we estimate these probabilities at 100% and 99% for GDP and labor productivity respectively. In contrast, the probability that the 80-quarter ahead responses to ε_{MRS} exceeds zero is only 61% for GDP and 19% for productivity; the corresponding probabilities for ε_{MP} are 53% for GDP and 73% for productivity. These results support the identifying assumption, used by Gali (1992, 1999) and Christiano, Eichenbaum, and Vigfuson (2003), that only technology shocks induce permanent shifts in output and/or productivity.

5.2. Cyclical Behavior of GDP and its Components

According to Table 4, about 72% of the variance of the 3-month ahead forecast error of GDP is explained by our three identified shocks. This fraction rises to 84% for the 60-month ahead forecast error. Recall that there are a total of six VAR innovations, so there are three remaining sources of variation (the γ_t vector) in system (2.4). Thus, our identified shocks do a reasonable job of accounting for output movements. The technology shock and the MRS shock are about equally important at the twelve-month horizon. However, at the 5-year horizon, the technology shock is the predominant driver of output variation. In contrast, the monetary policy shock accounts for a very small fraction of output variation at all horizons. This result supports results in Sims and Zha (1998) and Christiano, Eichenbaum, and Evans (1999) that monetary policy shocks account for, at best, only a small fraction of output fluctuation.

These patterns can also be seen in the GDP responses displayed in Figure 2, which displays impulse responses over a 20 quarter horizon. Note that the initial responses of GDP to ε_{TECH} and ε_{MRS} are similar in magnitude. However, the response to the technology shock persists, whereas the response to the MRS shock mean-reverts in 1-1/2 to 2 years. Finally, a contractionary monetary policy shock dampens GDP, although the posterior distribution of this response is quite spread out.

Turning to the key components of GDP, Table 4 shows that our three identified shocks account for over 70% of business fixed investment (equipment and software, investment structures) variation at the 5-year horizon, and over 60% of the corresponding variation in total consumption expenditures. Figure 2 shows that the responses of these GDP components look similar to the GDP responses: permanent response to ε_{TECH}, transient response to ε_{MRS}, negative but relatively small response to contractionary ε_{MP}. In contrast, the response of residential investment to both ε_{TECH} and ε_{MRS} mean-revert rather quickly after an initial positive response. In addition, residential investment displays a more pronounced response to the contractionary monetary policy shock. These responses reflect the high interest rate sensitivity of residential investment. As we shall discuss in section 5.5, below, monetary policy contracts in response to both an MRS shock and a technology shock, although the second response is with a delay of four to six quarters. These interest rate increases reverse the initially positive responses of residential investment to ε_{TECH} and ε_{MRS}.

One additional noteworthy result from Figure 2 is the gradual, hump-shaped response of consumption to permanent income drivers. In particular, real compensation has a gradual but permanent response to the technology shock, implying an substantial increase in permanent income. Thus, it is noteworthy that consumption expenditure has a rather small response to the technology shock on impact. Thereafter, consumption rises. This sluggish response of consumption to the technology shock would seem inconsistent with a simple formulation of the permanent income hypothesis, but would be consistent with the models of habit formation that are increasingly used in macroeconomic models. (See, for example, Boldrin, Christiano, and Fisher, 2001; and Fuhrer, 2000.)

5.3. Labor Markets

Figure 3 displays the responses of hours worked, payroll employment, and labor productivity to our three identified shocks. Note first that the MRS shock elicits an immediate rise in both hours and employment on impact. This effect, however appears to be transient, dissipating in about two years. In contrast there is virtually no response of hours or employment to a technology shock on impact. Thereafter, these measures of labor inputs rise steadily, reaching a new steady state in about 2 to 2-1/2 years. On the face of it, the permanent response of hours to the technology shock contradicts the theoretical premise that hours per capita should be stationary. This problem is not unique to our identification strategy, but generally arises in studies that use unadjusted hours data computed by the Bureau of Labor Statistics. Per-capita hours derived from these data are non-stationary, displaying a trend of about 0.6% per year.[22]

The initial response of labor inputs to technology shocks is a matter of some controversy in the literature. Basu, Fernald, and Kimball (2004) estimate that hours and payrolls fall with a technology shock on impact. Intuitively, higher productivity enables firms to meet demand with less labor. In contrast, Christiano, Eichenbaum and Vigfuson (2003) estimate a contemporaneous rise in labor inputs in response to a technology shock. Both of these papers identify the technology shock using long run restrictions, although the way these restrictions are implemented differs between the two papers. Our identification strategy does not impose long run restrictions, and our results are intermediate between these two earlier papers.

[22] Ramey and Francis (2006) construct a measure of per capita hours that adjusts for home production hours, hours spent in school, and other factors. In contrast with the unadjusted BLS data, their measure appears to be stationary.

Another question addressed by Figure 3 is whether the observed procyclicality of labor productivity is due to "labor hoarding" (a sluggish response of labor demand to cyclical movements in product demand) or simply due to procyclical technology shocks that directly drive productivity and output in the same direction. The impulse responses in Figure 3 tend to support the second explanation. They imply that labor productivity is driven almost exclusively by technology shocks. In particular, the productivity response to ε_{TECH} is positive over the first year with virtually 100% probability. In contrast, the responses of productivity to the MRS and monetary policy shocks are small and dissipate quickly. If labor hoarding were an important factor in explaining procyclical labor productivity, we would expect to see significant responses of productivity to these non-technology shocks. Thus, the small responses of productivity to ε_{MRS} and ε_{MP} provide little support for the labor hoarding story.

5.4. Inflation

According to Table 4, about 60% of the 5-year ahead variation in inflation is explained by our three identified shocks. The top row of Figure 4, which displays the responses of inflation to these three shocks, shows that both nominal and real shocks are important for inflation. Inflation rises strongly in response to ε_{MRS}. The inflationary response dissipates in two to three years. As a shock that induces short-term positive responses of both economic activity and prices, ε_{MRS} behaves as what Blanchard (1989) would call an aggregate demand shock.

An expansionary technology shock induces a fall in inflation for about a year and a half. This would be consistent with a model of monopolistically competitive firms that set prices as a markup over marginal cost. After the first 6 quarters or so, inflation appears to rise, and monetary policy responds by contracting.

What appears to be driving this inflation increase is the delayed response of consumption and business investment demand to the technology shock, discussed above in Section 5.2. In particular, while the technology shock induces an increase in productive capacity (both directly and as a result of the investment response), it also induces a rise in demand that exceeds the rise in capacity over the 5 year horizon displayed in the impulse responses. This results in an increasing output gap, defined as the difference between the actual output and the long-run sustainable level of output, given current productive capacity. The second row in Figure 4 displays the response of the output gap (measured as the difference between GDP and the Congressional Budget Office's measure of potential GDP). According to the figure, the output gap rises steadily for the two years following a technology shock, and remains elevated for at least another two years. Standard policy analysis would associate this sort of sustained output gap with inflationary pressures. This sort of association can be justified theoretically in models that generate a New Keynesian Phillips Curve (such as Gali and Gertler, 1999, and Eichenbaum and Fisher 2004).[23]

Finally, a notable result in Figure 4 is that a contractionary monetary policy shock is clearly deflationary, as theory would predict. That is, our identification approach shows no evidence of Sims's (1992) "price puzzle". An identification procedure for monetary policy shocks is said to display a price puzzle if it implies a pronounced and sustained inflationary response to a contractionary policy shock. Many procedures used in the literature to identify monetary policy shocks have this problem. The typical way to avoid a price puzzle is to include commodity prices, or some other forecaster of inflation, in the VAR. Our procedure avoids a price puzzle without explicitly including commodity prices. However, the principal components used in our FAVAR specification may span the information needed to forecast inflation.

5.5. Monetary Policy

As is common practice, we view the federal funds rate as the indicator of monetary policy. At short horizons, the most important of our three identified shocks for the federal funds rate is ε_{MP}. Specifically, ε_{MP} accounts for 34% of the 3-month ahead forecast variance of the federal funds rate at the median of the posterior distribution. (See Table 4.) By way of comparison, ε_{TECH} and ε_{MRS} account for just 7% and 14% of this variance, respectively. Figure 5 displays the responses of the funds rate to our three identified shocks. It shows that the response of the funds rate to the monetary policy shock is extremely short-lived, fully dissipating in about two quarters. At longer horizons, the MRS shock is by far the most important determinant of the stance of monetary policy, accounting for 59% of the 5-year ahead forecast variance of the funds rate (again, at the median of the posterior distribution). At this 5-year horizon, the corresponding variance percentage attributable to the technology shock falls to 9%, and the variance percentage of the monetary policy shock declines to 7%.

The response of the funds rate to ε_{MRS} follows the qualitative patterns predicted by a Taylor rule. In particular, the MRS shock induces a rise in both inflation and output without a concomitant increase in potential output. As a result, a Taylor Rule would predict monetary tightening. This is precisely what we find. In response to an ε_{MRS} impulse, the federal funds rate rises by over 100 basis points over four quarters. This response by the monetary authority is quite long-lived: the median funds rate remains about 70 basis points above its starting value even after five years. By all appearances, this looks like a classic

[23] While Gali and Gertler (1999) and Eichenbaum and Fisher (2004) associate inflationary pressures with increasing marginal costs, Gali and Gertler (1999) note that there is an approximate log-linear relationship between marginal costs and the output gap.

countercyclical response to a demand shock. What is puzzling about this result is that the policy response to ε_{MRS} is far longer-lived than the corresponding responses of either inflation or the output gap. This could be interpreted as evidence of policy inertia in the Fed's response to inflationary pressures.

Finally, Figure 5 shows that monetary policy becomes slightly accommodative on impact in response to an expansionary technology shock. In particular, the median response of the federal funds rate to ε_{Tech} is a 30 basis point decline. This is not surprising, given the deflationary impact of ε_{Tech} that we saw in Figure 4. Policy does not reliably turn restrictive until the inflation response turns positive, as described above in section 5.4.

5.6. Treasury Yields

We consider the one-, twelve-, and sixty-month zero-coupon U.S. Treasury yields as computed in the Fama-Bliss data base from CRSP. According to Table 4, between 66% and 75% of Treasury yield variation at the five-year horizon is explained jointly by our three identified shocks. The MRS shock is clearly the most important beyond the initial quarters. The last three rows of Figure 5 give the responses of these yields to the three identified shocks. Notice that the responses of the intermediate and long rates are similar both in shape and magnitude to the response of the short rate. As a result, the MRS shock induces approximately a parallel shift in the yield curve level. The monetary policy shock is only important at the very shortest horizon for shortest-term rates (the fed funds rate and the one-month yield) becoming less important for the longer-term rates. Hence, the monetary policy shock shifts the yield curve slope.

The yield responses to the technology shock are small and the distribution is spread around zero. For example, the probability that the one-month yield has a positive average response over the first year is 61%. (The corresponding probability for the 12- and 60-month yields are 66% and 53%, respectively.) So it would seem that treasury yields could easily respond in either direction. Perhaps this is not surprising. As noted by Evans and Marshall (2003), a technology shock moves real rates and expected inflation in opposite directions, so the theoretical predictions for nominal yields' responses are ambiguous. In Evans and Marshall (2003), the expected inflation effect tended to dominate, so technology shocks induced a fall in yields. In this study, however, we find that these two effects are of approximately the same magnitude, at least over the first year or so. As a result, the technology shock has a small effect on nominal yields.

5.7. Equity Markets

Our three identified shocks have relatively little explanatory power for stock prices. As shown in Table 4, they jointly explain only 26% of stock price variation at the five-year horizon (according to the median of the posterior distribution). They explain even less at shorter horizons: the corresponding variance fraction explained for the three month forecast error is only 9%. Thus, most variation in stock prices and returns are driven by factors other than our three identified impulses.

Having said this, the stock market does display significant responses to all three shocks. Figure 6 displays the responses of the S&P 500 index, the excess return to the market, and corporate profits. The stock market displays a pronounced positive response to an expansionary technology shock for about a year and a half. In particular, the median response of the level of the S&P 500 index over the four quarters averages a bit over one percentage point, rising to an average of 1.3 percentage points over the fifth through eighth quarters. The probability that these responses are positive is 96% and 88%, respectively. This response of the stock price index dissipates in 6 to 8 quarters, perhaps due to the contractionary response of monetary policy.

The mechanism underlying this stock price response is clear if we regard stock prices as discounted cash flows. In response to the technology shock, Figure 6 shows a positive response of profits (a proxy for cash flows), while Figure 5 shows a negligible response of long-term interest rates (a proxy for the discount factor). It follows that the discounted present value of the cash flow to equity holders must rise.

The response of the stock market to an expansionary MRS shock is rather different than the response to a technology shock. There may be a small initial rise in the stock market upon impact (the error bands are quite wide), but this response is immediately reversed. The subsequent movement of the stock market is negative, and the market fails to recover its pre-shock level even after five years. This negative outcome for equity markets appears to be driven by the strong contractionary response of monetary policy along with the concomitant increase in longer-term interest rates. In particular, while Figure 6 does show a positive response of profits to the MRS shock, the response of interest rates is much bigger. The resulting effect is to decrease the present value of cash flows to the equity holder. One might say that while "good news is good news" when the good news is an expansionary technology shock, "good news is bad news" for the market when the news is an expansionary MRS shock.[24]

[24] Contrast this result with that in Boyd, Hu, and Jagannathan (2005), where the market responds positively to good economic news in recessions, but tends to respond negatively to good economic news in expansions.

Finally, Figure 6 shows a substantial and fairly long-lived negative response of stock prices to a contractionary ε_{MP} shock. In particular, the median response of the S&P500 index in the eight quarters following the shock is a decline of over 2 percent. The probability of a negative response over this period is greater than 98%. The excess return to the market portfolio declines by about 70 basis points on impact with negative excess returns persisting for at least two quarters. These responses are pure discount-rate effects. (The response of profits to ε_{MP} is small and insignificant.) All this conforms roughly to the conventional wisdom that monetary contraction is bad for the stock market.

5.8. Univariate responses to model-based shock measures

A focus of this paper is to use our model-based shock measures η_t to simultaneously identify all three shocks ε_t, imposing the restriction that the elements of ε_t are mutually orthogonal. An alternative, and simpler, approach would be to compute the responses of macroeconomic variables directly to the innovation to each element of η_t individually. We call this the "single-η approach". This simpler approach ignores the correlations among the elements of η_t that are documented in Table 2. It also ignores possible contamination of $\eta_{i,t}$ by $\varepsilon_{j,t}$, $j \neq i$, and ignores possible measurement error $w_{i,t}$. In this section, we briefly discuss the implications of the single-η approach, and contrast its implications with the baseline approach of Section 2.

To implement the single-η approach, we estimate bivariate recursive VARs of the form

$$\begin{bmatrix} \eta_{i,t} \\ z_t \end{bmatrix} = \Phi(L) \begin{bmatrix} \eta_{i,t-1} \\ z_{t-1} \end{bmatrix} + \Sigma \upsilon_t, \quad E\upsilon_t\upsilon_t' = I \tag{5.1}$$

where $\eta_{i,t}$ is one of our three model-based shock measures, z_t is an endogenous variables whose responses we wish to explore, υ_t is a bivariate i.i.d. disturbance, and Σ is a lower triangular matrix. In this structure, $\upsilon_{1,t}$ is interpreted as the shock to $\eta_{i,t}$. We use four quarterly lags in this VAR.

Figure 7 presents selected responses from the single-η approach, and contrasts them with the corresponding responses using the baseline approach described in sections 2 through 4, above. While most of the responses to the model-based shock measures in framework (5.1) are qualitatively the same as in our baseline approach, there are several differences worthy of note. First, and most notably, the inflation response to the shock to η_{MP} in framework (5.1) displays a huge price puzzle. As shown in Figure 7, a contractionary shock to η_{MP} ("Single-Eta MP shock") induces a significant positive response to both the price level and the inflation rate. Inflation remains elevated for at least five years after the initial impulse.

This contrasts with the negative response to a contractionary ε_{MP} in both the price level and the inflation rate (also displayed in Figure 7).

Second, measures of consumption and investment appear to display permanent responses to η_{MP} in framework (5.1), which would seem to violate long run neutrality. Again, these differ from the response patterns to ε_{MP}. (Both are displayed in Figure 7.) Third, the federal funds rate displays essentially no response to η_{Tech}, the Basu-Fernald-Shapiro technology measure ("Single-Eta Tech shock" in Figure 7). If one believes that an expansionary technology shock ought to elicit an accommodative policy response, this finding would be puzzling.

More generally, if these anomalous responses are interpreted as evidence of misspecification, then one would not want to use the innovations to η_t as empirical counterparts to the structural shocks. Our baseline procedure would provide a more satisfactory alternative.

6. Conclusions

In this paper, we have proposed an approach to identifying multiple fundamental macroeconomic shocks. In the introduction, we listed a number of questions that could be fruitfully addressed by a multiple-shock approach. We find that the preponderance of variation in measures of economic activity can be explained as responses to the three shocks we identify: technology shocks, shocks to the marginal rate of substitution between consumption and leisure, and monetary policy shocks. In particular, these three shocks explain over 80% of the long-run variability in GDP and labor inputs, over 70% of the corresponding variability in the components of business fixed investment, and over 55% of the variability in the components of consumption and housing.

The traditional emphasis on technology shocks in macroeconomic modelling seems warranted if the focus is on the determinants of long-horizon variability in economic activity. In the shorter run, a more cyclical driver (here identified as our MRS shock) also needs to be considered. The association of technology shocks with permanent shocks to output and productivity is borne out by our analysis. More transitory responses are associated with our MRS shock, which is orthogonal to the technology shock.

We find no evidence that procyclical labor productivity is driven by "labor hoarding". Such an explanation would imply significant responses of productivity to non-technology shocks such as our MRS shock. In our results however, the only important driver of productivity is the technology shock. Furthermore, technology shocks are neither expansionary nor contractionary on impact for labor inputs. Rather, inputs have a negligible contemporaneous response to ε_{TECH}. This result is midway between that found by Basu, Fernald, and Kimball (2004) and that reported by Christiano, Eichenbaum, and Vigfuson (2003).

Monetary policy shocks account for a rather small fraction of output variation. Furthermore, these shocks are important for monetary policy itself only in the short run. Over a longer horizon, most variation in the federal funds rate is due to the endogenous response of monetary policy to an MRS shock. The central bank "leans against the wind" in response to aggregate demand shocks.

About 60% of long-run variation in inflation is explained by our three identified shocks. Both nominal shocks (ε_{MP}) and real shocks (ε_{TECH} and ε_{MRS}) are important determinants of price level and inflation. The preponderance of variation in Treasury yields at all maturities is explained by our three shocks, with the MRS shock (which we think of as analogous to an "aggregate demand" shock) most important. In contrast, most variation in stock prices and returns is driven by factors other than those identified in this study. Nonetheless, there is evidence that the stock market displays significant responses to all three shocks. As expected, expansionary technology shocks induce increases in stock prices while contractionary monetary policy shocks are bad for the market. The market reacts negatively to the "good news" of an expansionary MRS shock (after 2-3 quarters).

While the results of this paper are intriguing, they raise as many questions as they answer. Would the results change if more fundamental shocks were added (for example, fiscal policy shocks or investment-specific technology shocks)? What is the interpretation of the MRS shock? We find that it behaves rather differently than the technology shock, suggesting that it probably is not simply a shock to home production technology. But is it best interpreted as a preference shock (as argued by Hall, 1997), or as a shock to implicit labor taxes or labor market frictions? Are there other fundamental shocks that can explain the remaining stock return variation, or does the stock market largely follow its own dynamic, with most of its volatility orthogonal to the macroeconomy? All of these questions await future work.

7. Appendix: Estimation of the Posterior Distribution Assuming an Uninformative Prior

In this appendix, we construct the posterior distribution for the model parameters $\{\Sigma_u, B, \Sigma_w, C\}$, assuming an uninformative prior. As discussed in Section 3, we treat $\widehat{Y}_t$ and η_t as known data.

It is first useful to fix some notation. Let $\widetilde{Y}$ $([T+l] \times n)$ denote a matrix containing the factor series $\widehat{Y}_t$ used in the VAR. (Here, T denotes the number of usable observations, l denotes the number of lags in the VAR, and n denotes the number of factors in the VAR.) To write the VAR in regression notation, let $q \equiv nl + 1$, the number of regressors per equation, let the $(T \times n)$ matrix of dependent variables in the VAR be denoted Y,

$$Y \equiv \begin{bmatrix} \widetilde{Y}_{l+1,1} & \cdots & \widetilde{Y}_{l+1,n} \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \widetilde{Y}_{l+T,1} & & \widetilde{Y}_{l+T,n} \end{bmatrix}$$

let the $(T \times q)$ matrix of VAR regressors be denoted X,

$$X \equiv \begin{bmatrix} 1 & \widetilde{Y}_{l,1} & \widetilde{Y}_{l-1,1} & \cdots & \widetilde{Y}_{1,1} & \widetilde{Y}_{l,2} & \widetilde{Y}_{l-1,2} & \cdots & \widetilde{Y}_{1,2} & \widetilde{Y}_{l,3} & \cdots & \widetilde{Y}_{1,n} \\ 1 & \widetilde{Y}_{l+1,1} & \widetilde{Y}_{l,1} & \cdots & \widetilde{Y}_{2,1} & \widetilde{Y}_{l+1,2} & \widetilde{Y}_{l,2} & \cdots & \widetilde{Y}_{2,2} & \widetilde{Y}_{l+1,3} & \cdots & \widetilde{Y}_{2,n} \\ \cdot & \cdot & & & & & & & & & & \cdot \\ \cdot & \cdot & & & & & & & & & & \cdot \\ \cdot & \cdot & & & & & & & & & & \cdot \\ 1 & \widetilde{Y}_{l+T-1,1} & \widetilde{Y}_{l+T-2,1} & \cdots & \widetilde{Y}_{T,1} & \widetilde{Y}_{l+T-1,2} & \widetilde{Y}_{l+T-2,2} & \cdots & \widetilde{Y}_{T,2} & \widetilde{Y}_{l+T-1,3} & & \widetilde{Y}_{T,N} \end{bmatrix},$$

and let the $(T \times m)$ matrix of model-based shocks be denoted H,

$$H \equiv \begin{bmatrix} \eta_{1,1} & \cdots & \eta_{1,m} \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \eta_{T,1} & & \eta_{T,m} \end{bmatrix}.$$

Our goal is to compute the joint posterior density $p(C, \Sigma_w, B, \Sigma_u)$, which can be written as follows:[25]

$$p(C, \Sigma_w, B, \Sigma_u) = p(C|\Sigma_w, B, \Sigma_u)\, p(\Sigma_w|B, \Sigma_u)\, p(B|\Sigma_u)\, p(\Sigma_u) \tag{7.1}$$

[25] All densities in equation (7.1) are conditional on the data $\{Y, X, H\}$. This dependency is not noted explicitly.

We assume uninformative priors in the usual way:

$$prior\left(\Sigma_u\right) \propto \left|\Sigma_u\right|^{-(n+1)/2} \tag{7.2}$$

$$prior(B) = \text{constant} \tag{7.3}$$

$$prior\left(\Sigma_w\right) \propto \left|\Sigma_w\right|^{-(m+1)/2} \tag{7.4}$$

$$prior(C) = \text{constant} \tag{7.5}$$

The reduced form of the VAR is given by the regression equation

$$Y = XB + U \tag{7.6}$$

where matrix U contains the $n \times 1$ i.i.d. error process u_t as $U = (u_1, u_2, \cdots, u_T)'$, and it is assumed that

$$u_t \sim N\left(0, \Sigma_u\right). \tag{7.7}$$

In equation (7.6), the coefficient matrix B has dimension $(q \times n)$. The rows of B correspond to the regressors X; the columns correspond to the n equations. Let $\widehat{B}$ denotes the matrix of OLS estimates of the VAR slope coefficients

$$\widehat{B} \equiv \left(X'X\right)^{-1} X'Y \tag{7.8}$$

and let S denotes T times the sample covariance matrix of the VAR disturbances

$$S \equiv \left(Y - X\widehat{B}\right)' \left(Y - X\widehat{B}\right).$$

Finally, let B_s and $\widehat{B}_s$ denote the vectors formed by stacking the columns of B and $\widehat{B}$, respectively.

Zellner (1971) shows that, given the priors (7.2) and (7.3), the posterior distribution $p\left(\Sigma_u\right)$ is inverted Wishart with parameter S. He also shows that, conditional on Σ_u, the posterior distribution $p\left(B_s|\Sigma_u\right)$ is multivariate normal with mean $\widehat{B}_s$ and variance-covariance matrix $\Sigma_u \otimes \left(X'X\right)^{-1}$.

We can use Zellner's (1971) logic to derive the remaining components of the joint posterior distribution (7.1). Equation (2.2) can be written

$$H = \widetilde{U}C + W. \tag{7.9}$$

In equation (7.9), $\widetilde{U}$ is a matrix whose columns contain contemporaneous and K lags of U, W stacks the $m \times 1$ i.i.d. measurement error process w_t as $W = (w_1, w_2, \cdots, w_T)'$, and it is assumed that

$$W \sim N\left(0, \Sigma_w\right). \tag{7.10}$$

We follow the same steps as we used to derive $p(\Sigma_u)$ and $p(B|\Sigma_u)$, except that we condition on B. (It turns out that Σ_u does not directly affect the conditional distribution of C and Σ_w.) For a given B, let us write

$$U(B) \equiv Y - XB$$

$$\widehat{C}(B) \equiv \left(\widetilde{U}(B)'\widetilde{U}(B)\right)^{-1} \widetilde{U}(B)' H$$

and

$$V(B) \equiv \left(H - \widetilde{U}(B)\widehat{C}(B)\right)' \left(H - \widetilde{U}(B)\widehat{C}(B)\right)$$

(where $\widetilde{U}(B)$ contains the contemporaneous and K lags of $U(B)$). The interpretation of these objects is as follows: $U(B)$ is the matrix of residuals implied by equation (7.6) given the observed data $\{Y, X\}$ and a particular choice of B; $\widehat{C}(B)$ is the estimate of C that one would obtain from $U(B)$ and H if one estimated equation (7.9) via OLS; $V(B)$ is the moment matrix of the residuals from this OLS estimation of equation (7.9). Conditional on B, the objects $\left\{U(B), \widehat{C}(B), V(B)\right\}$ are functions of the data, so can be treated as known quantities. Therefore, by logic analogous to Zellner (1971), posterior distribution $p(\Sigma_w|B)$ is inverted Wishart with parameter $V(B)$, and posterior distribution $\mathrm{p}(C_s|\Sigma_w, B)$ is multivariate normal with mean $\widehat{C}(B)_s$ and variance-covariance matrix $\Sigma_w \otimes \left(\widetilde{U}(B)'\widetilde{U}(B)\right)^{-1}$.

One draws from the posterior distribution for $\{C, \Sigma_w, B, \Sigma_u\}$ as follows:

1. Draw Σ_u from the inverted Wishart density with parameter S, which is a function of data.

2. Given this draw of Σ_u, draw B_s from the multivariate normal distribution with mean $\widehat{B}_s$ and variance-covariance matrix $\Sigma_u \otimes (X'X)^{-1}$.

3. Given this draw of B, draw Σ_w from the inverted Wishart density with parameter $V(B)$.

4. Given these draws of B and Σ_w, draw C_s from the multivariate normal distribution with mean $\widehat{C}(B)_s$ and variance-covariance matrix $\Sigma_w \otimes \left(\widetilde{U}(B)'\widetilde{U}(B)\right)^{-1}$.

8. Data Appendix

We use quarterly data from 1967:Q1 through 2000:Q4.[26] As described in the text, we use two (overlapping) data sets. The first data set consists of the 190 series used to construct the

[26] We start in 1967 because many of the series used to generate the principal components used in the FAVAR specification are available only from 1967 onward.

factors in the FAVAR model. Specifically, the six factors comprising vector $\widehat{Y}_t$ in equation (2.18) are the first six principal components of these 190 data series. 154 of these series are monthly, and the remaining 36 are quarterly. To facilitate computation of principal components, each of these data series is rendered stationary. Table 1A lists these data in detail, along with the stationarity-inducing transformations used.

The second data set is used to construct the series z_t (in equation (2.17), whose impulse responses are to be computed. The data used are as follows:

- Data on real GDP and its components (total consumption expenditure, investment in equipment and software, investment in structures, residential investment) are quarterly data (seasonally adjusted in chained 2000 dollars) from the Bureau of Economic Analysis (BEA). The output gap is the log of real GDP minus the log of the Congressional Budget Office's measure of potential GDP.

- Our measure of the price level is the GDP chain-type price index from BEA. The 3 month inflation rate is the log difference of the price level.

- Labor productivity is seasonally adjusted business sector output per hour of all persons (seasonally adjusted) from the Bureau of Labor Statistics (BLS)

- Employment is total nonfarm employment, and payroll hours series is the aggregate total private hours per week index. Both of these are seasonally adjusted data from the BLS establishment survey.

- The real compensation series is business sector real compensation per hour from the BEA, deflated by the GDP chain-type price index.

- The Federal Funds Rate is the effective funds rate from the Federal Reserve Bank of New York. The 1- 12- and 60-month zero coupon Treasury yields are from the Fama-Bliss zero coupon bond files in the CRSP database. The S&P500 Stock Index is from Standard and Poor's. All of these financial data series are converted to quarterly series by sampling the last business day of each quarter.

- Our measure of the excess stock market return is the first Fama-French factor from Kenneth French's web page

  http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

These data are rendered quarterly by sampling the last month of quarter.

- Profits is the BEA measure of corporate profits (pre-tax) from current production, seasonally adjusted.

For all series other than the inflation rate, interest rates, and excess stock returns, we estimate the VAR in log-differences, and then we cumulated the impulse responses to display the responses of log-levels.

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Table 1: Granger-Causality Tests for MRS Measure

Explanatory Variable	# Lags	Marginal Significance of F-test
Detrended GDP	4	0.742
	5	0.891
	6	0.715
Fed Funds Rate	4	0.356
	5	0.582
	6	0.510
Term Spread	4	0.199
	5	0.165
	6	0.202

Notes: This table displays the marginal significance of exclusion F-statistics for the following Granger-Causality regressions

$$\eta_{MRS,t} = \sum_{j=1}^{N} \alpha_j \eta_{MRS,t-j} + \beta_j X_{t-j} + w_{i,t},$$

where $N = 4, 5$, or 6; the explanatory variable X is either detrended GDP, the federal funds rate, or the term spread (defined as the difference between the 5-year Treasury Yield and the federal funds rate); and the F-statistic tests the hypothesis $\beta_j = 0, \forall j = 1, ..., N$.

Table 2: Correlation Matrix of the Model-Based Shock Measures

	η_{MP}	η_{MRS}	η_{TECH}
η_{MP}	1.0		
η_{MRS}	0.11	1.0	
η_{TECH}	-0.037	0.062	1.0

Table 3: R^2s For Regression of Model-Based Shock Measures on VAR Residuals

Shock Measure	R^2 when regressed on VAR residuals	F-test
η_{MP}	54.1%	29.7 (0.000)
η_{MRS}	53.6%	61.2 (0.000)
η_{TECH}	52.3%	140.7 (0.000)

Notes: The second column displays the R^2s for the regressions $\eta_t = C_0 u_t + C_1 u_{t-1} + ... + C_4 u_{t-4} + w_t$ (equation (2.9)), where η_t denotes the 3×1 vector of model-based measures, u_t denotes the 6×1 vector of VAR residuals, and w_t denotes the 3×1 vector of residuals.. The third column displays the F-statistic testing the hypothesis that the given row of $C_0 = 0$.

Table 4

Fraction of Variance of Endogenous Variables Accounted for by the Three Identified Shocks

Notes: For each of the variables listed, the table gives the median fraction of 3-, 12, and 60-month ahead forecast variance accounted for by the three identified shocks, ε_{MP}, ε_{MRS}, and ε_{TECH}, according to the posterior distribution. The fourth line in each panel gives the median fraction of each forecast variance accounted for by the three shocks collectively. The two numbers in parentheses following each median statistic give the 95% and 5% quantiles of the posterior distribution for each forecast variance fraction. These statistics were computed using 500 draws from the posterior distribution of the model's parameters.

Real GDP

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.049 (0.233,0.001)	0.064 (0.224,0.021)	0.124 (0.433,0.014)
Shock to MRS	0.282 (0.514,0.088)	0.328 (0.609,0.087)	0.107 (0.411,0.024)
Shock to Tech	0.344 (0.573,0.151)	0.422 (0.702,0.176)	0.527 (0.774,0.208)
Total of 3 Shocks	0.721 (0.779,0.632)	0.861 (0.909,0.763)	0.844 (0.928,0.648)

Total Consumption Expenditures

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.009 (0.076,0.000)	0.112 (0.322,0.014)	0.081 (0.330,0.013)
Shock to MRS	0.305 (0.478,0.121)	0.137 (0.369,0.029)	0.060 (0.284,0.011)
Shock to Tech	0.156 (0.332,0.033)	0.372 (0.593,0.134)	0.399 (0.650,0.162)
Total of 3 Shocks	0.492 (0.598,0.365)	0.661 (0.768,0.497)	0.617 (0.791,0.400)

Investment Equip & Software

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.027 (0.116,0.001)	0.027 (0.136,0.008)	0.058 (0.274,0.011)
Shock to MRS	0.339 (0.430,0.221)	0.535 (0.702,0.307)	0.289 (0.576,0.074)
Shock to Tech	0.015 (0.095,0.000)	0.128 (0.357,0.014)	0.303 (0.606,0.070)
Total of 3 Shocks	0.404 (0.488,0.307)	0.721 (0.801,0.602)	0.712 (0.864,0.490)

Investment Structures

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.031 (0.095,0.001)	0.034 (0.186,0.002)	0.030 (0.229,0.003)
Shock to MRS	0.074 (0.137,0.028)	0.346 (0.512,0.186)	0.461 (0.717,0.185)
Shock to Tech	0.020 (0.061,0.001)	0.074 (0.246,0.005)	0.179 (0.488,0.016)
Total of 3 Shocks	0.138 (0.201,0.089)	0.497 (0.626,0.361)	0.735 (0.861,0.548)

Residential Investment

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.005 (0.048,0.000)	0.232 (0.419,0.086)	0.164 (0.340,0.058)
Shock to MRS	0.245 (0.336,0.133)	0.104 (0.233,0.052)	0.240 (0.513,0.036)
Shock to Tech	0.061 (0.179,0.004)	0.225 (0.412,0.050)	0.147 (0.313,0.039)
Total of 3 Shocks	0.328 (0.399,0.257)	0.591 (0.698,0.459)	0.605 (0.808,0.316)

Table 4 (continued)

Labor Productivity

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.019 (0.099,0.000)	0.041 (0.190,0.012)	0.044 (0.207,0.007)
Shock to MRS	0.019 (0.118,0.000)	0.025 (0.104,0.005)	0.045 (0.209,0.008)
Shock to Tech	0.464 (0.552,0.347)	0.435 (0.569,0.289)	0.337 (0.537,0.156)
Total of 3 Shocks	0.530 (0.600,0.446)	0.536 (0.652,0.413)	0.472 (0.656,0.299)

Payroll Employment

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.098 (0.290,0.007)	0.031 (0.139,0.010)	0.085 (0.369,0.010)
Shock to MRS	0.522 (0.655,0.360)	0.592 (0.764,0.319)	0.212 (0.545,0.050)
Shock to Tech	0.028 (0.186,0.000)	0.161 (0.422,0.029)	0.440 (0.741,0.158)
Total of 3 Shocks	0.688 (0.755,0.601)	0.821 (0.882,0.702)	0.831 (0.912,0.639)

Payroll Hours

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.094 (0.282,0.007)	0.040 (0.147,0.012)	0.072 (0.314,0.013)
Shock to MRS	0.537 (0.673,0.373)	0.595 (0.768,0.347)	0.247 (0.552,0.068)
Shock to Tech	0.016 (0.140,0.000)	0.139 (0.391,0.026)	0.405 (0.715,0.137)
Total of 3 Shocks	0.690 (0.764,0.583)	0.816 (0.884,0.679)	0.803 (0.902,0.621)

Real Wage

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.046 (0.094,0.008)	0.050 (0.141,0.006)	0.109 (0.373,0.006)
Shock to MRS	0.002 (0.016,0.000)	0.044 (0.122,0.009)	0.167 (0.443,0.011)
Shock to Tech	0.003 (0.024,0.000)	0.013 (0.042,0.004)	0.095 (0.334,0.005)
Total of 3 Shocks	0.055 (0.106,0.018)	0.120 (0.226,0.040)	0.460 (0.691,0.198)

Inflation

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.045 (0.162,0.001)	0.037 (0.117,0.008)	0.216 (0.419,0.067)
Shock to MRS	0.007 (0.061,0.000)	0.095 (0.260,0.022)	0.164 (0.370,0.054)
Shock to Tech	0.130 (0.229,0.035)	0.194 (0.356,0.070)	0.171 (0.341,0.060)
Total of 3 Shocks	0.199 (0.307,0.108)	0.362 (0.502,0.210)	0.596 (0.774,0.390)

Federal Funds Rate

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.342 (0.485,0.186)	0.147 (0.302,0.066)	0.074 (0.227,0.024)
Shock to MRS	0.141 (0.329,0.032)	0.511 (0.647,0.345)	0.594 (0.761,0.302)
Shock to Tech	0.068 (0.194,0.002)	0.047 (0.146,0.010)	0.090 (0.351,0.013)
Total of 3 Shocks	0.577 (0.648,0.498)	0.726 (0.795,0.628)	0.803 (0.891,0.617)

1-month Treasury Yield

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.164 (0.254,0.084)	0.114 (0.248,0.047)	0.071 (0.203,0.023)
Shock to MRS	0.087 (0.189,0.025)	0.378 (0.511,0.251)	0.540 (0.725,0.262)
Shock to Tech	0.015 (0.064,0.000)	0.032 (0.123,0.009)	0.108 (0.376,0.011)
Total of 3 Shocks	0.281 (0.357,0.211)	0.552 (0.641,0.449)	0.751 (0.860,0.575)

Table 4 (continued)

12- month Treasury Yield

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.247 (0.373,0.122)	0.150 (0.337,0.048)	0.079 (0.214,0.026)
Shock to MRS	0.152 (0.288,0.052)	0.421 (0.569,0.251)	0.546 (0.741,0.294)
Shock to Tech	0.008 (0.055,0.000)	0.021 (0.128,0.004)	0.077 (0.336,0.008)
Total of 3 Shocks	0.422 (0.504,0.334)	0.624 (0.715,0.513)	0.746 (0.867,0.570)

60- month Treasury Yield

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.121 (0.235,0.084)	0.133 (0.314,0.026)	0.076 (0.221,0.023)
Shock to MRS	0.137 (0.245,0.025)	0.339 (0.505,0.192)	0.511 (0.709,0.277)
Shock to Tech	0.005 (0.047,0.000)	0.015 (0.088,0.002)	0.038 (0.210,0.006)
Total of 3 Shocks	0.287 (0.363,0.196)	0.522 (0.628,0.394)	0.662 (0.823,0.467)

S&P500 Stock Index

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.040 (0.101,0.008)	0.081 (0.172,0.026)	0.086 (0.162,0.038)
Shock to MRS	0.010 (0.046,0.000)	0.059 (0.118,0.028)	0.092 (0.152,0.040)
Shock to Tech	0.033 (0.095,0.003)	0.049 (0.097,0.019)	0.074 (0.138,0.024)
Total of 3 Shocks	0.094 (0.176,0.047)	0.199 (0.334,0.117)	0.262 (0.355,0.181)

Excess Stock Market Return

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.066 (0.141,0.017)	0.078 (0.143,0.031)	0.081 (0.144,0.036)
Shock to MRS	0.006 (0.044,0.000)	0.043 (0.087,0.017)	0.065 (0.112,0.033)
Shock to Tech	0.047 (0.100,0.007)	0.067 (0.116,0.025)	0.079 (0.134,0.038)
Total of 3 Shocks	0.132 (0.194,0.076)	0.193 (0.266,0.128)	0.233 (0.311,0.162)

Table 5: Long-Run Responses to 1 SD Shock

	GDP	Productivity
Technology Shock	58 bps (1.00)	31 bps (0.99)
MRS Shock	7 bps (0.61)	-15 bps (0.19)
MP Shock	3 bps (0.53)	12 bps (0.73)

Notes: This table gives the median 80-quarter ahead responses of GDP and labor productivity to a one standard deviation impulse to each of the three shocks listed in the left-most column. The numbers in parenthesis give the probability that this 80-quarter ahead response is positive according to the Bayesian posterior distribution.

Table 1A: Data Used in Constructing FAVAR Factors

Panel A: Monthly Data Series

Data Description	Transformation
Personal Consumption Expenditures (SAAR, Bil.Chn.2000$)	log 1st diff
Personal Consumption Expenditures: Durable Goods (SAAR, Bil.Chn.2000$)	log 1st diff
Personal Consumption Expenditures: Nondurable Goods (SAAR,Bil.Chn.2000$)	log 1st diff
Personal Consumption Expenditures: Services (SAAR, Bil.Chn.2000$)	log 1st diff
Real Disposable Personal Income (SAAR, Bil.Chn.2000$)	log 1st diff
Value of Public Construction Put in Place (SAAR, Mil.Chn. $)	log 1st diff
Value of Private Construction Put in Place (SAAR, Mil. Chn. $)	log 1st diff
Manufacturers' Shipments of Mobile Homes (SAAR, Thous.Units)	log
Housing Starts (SAAR, Thous.Units)	log
Housing Starts: Midwest (SAAR, Thous.Units)	log
Housing Starts: Northeast (SAAR, Thous.Units)	log
Housing Starts: South (SAAR, Thous.Units)	log
Housing Starts: West (SAAR, Thous.Units)	log
Industrial Production Index (SA, 1997=100)	log 1st diff
Industrial Production: Consumer Goods (SA, 1997=100)	log 1st diff
Industrial Production: Durable Consumer Goods (SA, 1997=100)	log 1st diff
Industrial Production: Nondurable Consumer Goods (SA, 1997=100)	log 1st diff
Industrial Production: Business Equipment (SA, 1997=100)	log 1st diff
Industrial Production: Materials (SA, 1997=100)	log 1st diff
Industrial Production: Durable Goods Materials (SA, 1997=100)	log 1st diff
Industrial Production: Nondurable Goods Materials (SA, 1997=100)	log 1st diff
Industrial Production: Nonindustrial Supplies (SA, 1997=100)	log 1st diff
Industrial Production: Mining (SA, 1997=100)	log 1st diff
Industrial Production: Final Products (SA, 1997=100)	log 1st diff
Industrial Production: Durable Goods [NAICS] (SA, 1997=100)	log 1st diff
Industrial Production: Manufacturing [SIC] (SA, 1997=100)	log 1st diff
Industrial Production: Nondurable Manufacturing (SA, 1997=100)	log 1st diff
Industrial Production: Final Products and Nonindustrial Supplies (SA, 1997=100)	log 1st diff
Industrial Production: Electric and Gas Utilities (SA, 1997=100)	log 1st diff
All Employees: Construction (SA, Thous)	log 1st diff
All Employees: Durable Goods Manufacturing (SA, Thous)	log 1st diff
All Employees: Financial Activities (SA, Thous)	log 1st diff
All Employees: Goods-producing Industries (SA, Thous)	log 1st diff
All Employees: Government (SA, Thous)	log 1st diff
All Employees: Manufacturing (SA, Thous)	log 1st diff
All Employees: Mining (SA, Thous)	log 1st diff
All Employees: Total Nonfarm (SA, Thous)	log 1st diff
All Employees: Nondurable Goods Manufacturing (SA, Thous)	log 1st diff
All Employees: Total Private Industries (SA, Thous)	log 1st diff

All Employees: Retail Trade (SA, Thous)	log 1st diff
All Employees: Service-providing Industries (SA, Thous)	log 1st diff
All Employees: Aggregate of categories	log 1st diff
Civilian Employment: Nonagricultural Industries: 16 yr + (SA, Thous)	log 1st diff
Ratio: Help-Wanted Advertising in Newspapers/Number Unemployed (SA)	log 1st diff
Average Weekly Hours: Overtime: Manufacturing (SA, Hrs)	1st diff
Average Weekly Hours: Manufacturing (SA, Hrs)	1st diff
ISM Mfg: PMI Composite Index (SA, 50+ = Econ Expand)	level
ISM Mfg: Employment Index (SA, 50+ = Econ Expand)	level
ISM Mfg: Inventories Index (SA, 50+ = Econ Expand)	level
ISM Mfg: New Orders Index (SA, 50+ = Econ Expand)	level
ISM Mfg: Production Index (SA, 50+ = Econ Expand)	level
Real Retail Sales: Durable Goods (SA, Mil.Chain.2000$)	log 1st diff
Retail Sales: Retail Trade (SA, Spliced, Mil.Chn 2000$)	log 1st diff
Real Retail Sales: Nondurable Goods (SA, Mil.Chain.2000$)	log 1st diff
Real Inventories: Mfg: Durable Goods Industries (SA, EOP, Spliced, Mil Chn 2000$)	log 1st diff
Real Manufacturing & Trade Inventories: Mfg Industries (SA, EOP, Spliced, Mil.Chn 2000$)	log 1st diff
Real Mfg Inventories: Nondurable Goods Industries (SA, EOP, Spliced, Mil.Chn 2000$)	log 1st diff
Real Inventories: Retail Trade Industries (SA, EOP, Spliced, Mil.Chn 2000$)	log 1st diff
Real Manufacturing & Trade Inventories: Industries (SA, EOP, Spliced, Mil.Chn 2000$)	log 1st diff
Real Inventories: Merchant Wholesale Trade Industries (SA, EOP, Spliced, Mil.Chn 2000$)	log 1st diff
Real Inventories/Sales Ratio: Manufacturing Industries (SA, Spliced, Chained 2000$)	1st diff
Inventories/Sales Ratio: Retail Trade Industries (SA, Spliced, Chained 2000$)	1st diff
Real Manufacturing & Trade: Inventories/Sales Ratio (SA, Spliced, Chained 2000$)	1st diff
Inventories/Sales Ratio: Merchant Wholesale Trade Industries(SA, Chained 2000$)	1st diff
Real Sales: Mfg: Durable Goods Industries(SA, Spliced, Mil.Chn 2000$)	log 1st diff
Real Sales: Manufacturing Industries (SA, Spliced, Mil.Chn 2000$)	log 1st diff
Real Sales: Mfg: Nondurable Goods Industries (SA, Spliced, Mil.Chn 2000$)	log 1st diff
Real Manufacturing & Trade Sales: All Industries (SA, Spliced, Mil.Chn 2000$)	log 1st diff
Real Sales: Merchant Wholesalers: Durable Gds Industrs (SA, Spliced, Mil.Chn 2000$)	log 1st diff
Real Sales: Merchant Wholesale Trade Industries (SA, Spliced, Mil.Chn 2000$)	log 1st diff
Real Sales: Merch Wholesale: Nondurable Goods Industries (SA, Mil.Chn 2000$)	log 1st diff
Real Personal Income Less Transfer Payments (SAAR, Bil.Chn.2000$)	log 1st diff
PCE: Durable Goods: Motor Vehicles and Parts (SAAR, Mil.Chn.2000$)	log 1st diff
Mfrs New Orders: Durable Goods (SA, Mil.Chn.2000.$)	log 1st diff
Manufacturers New Orders: Consumer Goods & Materials (SA, Mil. 1982$)	log 1st diff
Manufacturers New Orders: Nondefense Capital Goods (SA, Mil. 1982$)	log 1st diff
New Pvt Housing Units Authorized by Building Permit (SAAR, Thous.Units)	log
Capacity Utilization: Manufacturing [SIC] (SA, Percent of Capacity)	1st diff
Index of Help-Wanted Advertising in Newspapers (SA,1987=100)	log 1st diff
Civilian Unemployment Rate: 16 yr + (SA, %)	1st diff
University of Michigan: Consumer Expectations (NSA, 66Q1=100)	level
Civilians Unemployed for Less Than 5 Weeks (SA, Thous.)	level
Civilians Unemployed for 15-26 Weeks (SA, Thous.)	level
Civilians Unemployed for 5-14 Weeks (SA, Thous.)	level
Average {Mean} Duration of Unemployment (SA, Weeks)	level
Civilians Unemployed for 15 Weeks and Over (SA, Thous.)	level
Civilians Unemployed for 27 Weeks and Over (SA, Thous.)	level

Adjusted Monetary Base (SA, Mil.$)	log 2nd diff
Adjusted Nonborrowed Reserves of Depository Institutions (SA, Mil.$)	log 2nd diff
Adjusted Nonborrowed Reserves Plus Extended Credit (SA, Mil.$)	log 2nd diff
Adjusted Reserves of Depository Institutions (SA, Mil.$)	log 2nd diff
Adj Monetary Base inc Deposits to Satisfy Clearing Bal Contracts (SA, Bil.$)	log 2nd diff
Money Stock: M1 (SA, Bil.$)	log 2nd diff
Real Money Stock: M2 (SA, Bil.Chn.2000$)	log 1st diff
Money Stock: M3 (SA, Bil.$)	log 2nd diff
Nominal Broad Trade-Weighted Exchange Value of the US$ (JAN 97=100)	log 1st diff
Foreign Exchange Rate: United Kingdom (US$/Pound)	log 1st diff
Moody's Seasoned Aaa Corporate Bond Yield (% p.a.)	1st diff
Moody's Seasoned Baa Corporate Bond Yield (% p.a.)	1st diff
Moody's Seasoned Aaa Corporate Bond Yield - Federal Funds Rate(% p.a.)	level
Moody's Seasoned Baa Corporate Bond Yield - Federal Funds Rate (% p.a.)	level
S&P: Composite 500, Dividend Yield (%)	level
Stock Price Index: Standard & Poor's 500 Composite (1941-43=10)	log 1st diff
S&P: 500 Composite, P/E Ratio, 4-Qtr Trailing Earnings	level
Stock Price Index: NYSE Composite (Avg, Dec. 31, 2002=5000)	log 1st diff
Stock Price Index: Standard & Poor's 400 Industrials (1941-43=10)	log 1st diff
3-Month Treasury Bills, Secondary Market (% p.a.)	1st diff
6-Month Treasury Bills, Secondary Market (% p.a.)	1st diff
3-Month Treasury Bills - Federal Funds Rate, (% p.a.)	level
6-Month Treasury Bills - Federal Funds Rate (% p.a.)	level
1-Year Treasury Bill Yield at Constant Maturity (% p.a.)	1st diff
5-Year Treasury Note Yield at Constant Maturity (% p.a.)	1st diff
1-Year Treasury Bill Yield at Constant Maturity - Federal Funds Rate (% p.a.)	level
5-Year Treasury Note Yield at Constant Maturity - Federal Funds Rate (% p.a.)	level
10-Year Treasury Note Yield at Constant Maturity - Federal Funds Rate (% p.a.)	level
PPI: Crude Materials for Further Processing (SA, 1982=100)	log 2nd diff
PPI: Finished Consumer Goods (SA, 1982=100)	log 2nd diff
CPI-U: Apparel (SA, 1982-84=100)	log 2nd diff
CPI-U: Commodities (SA, 1982-84=100)	log 2nd diff
CPI-U: Durables (SA, 1982-84=100)	log 2nd diff
CPI-U: Services (SA, 1982-84=100)	log 2nd diff
CPI-U: Medical Care (SA, 1982-84=100)	log 2nd diff
CPI-U: All Items Less Food (SA, 1982-84=100)	log 2nd diff
CPI-U: All Items Less Medical Care (SA, 1982-84=100)	log 2nd diff
CPI-U: All Items Less Shelter (SA, 1982-84=100)	log 2nd diff
CPI-U: Transportation (SA, 1982-84=100)	log 2nd diff
PCE: Durable Goods: Chain Price Index (SA, 2000=100)	log 2nd diff
PCE: Personal Consumption Expenditures: Chain Price Index (SA, 2000=100)	log 2nd diff
PCE: Nondurable Goods: Chain Price Index (SA, 2000=100)	log 2nd diff
PCE: Services: Chain Price Index (SA, 2000=100)	log 2nd diff
Avg Hourly Earnings: Construction (SA, $/Hr)	log 2nd diff
Avg Hourly Earnings: Manufacturing (SA, $/Hr)	log 2nd diff
Commercial & Industrial Loans Outstanding (EOP, SA, Mil.Chn.2000 $)	1st diff
Money Stock: M2 (SA, Bil.$)	log 2nd diff
10-Year Treasury Note Yield at Constant Maturity (% p.a.)	1st diff

Federal Funds [effective] Rate (% p.a.)	1st diff
PPI: Intermediate Materials, Supplies and Components (SA, 1982=100)	log 2nd diff
PPI: Finished Goods (SA, 1982=100)	log 2nd diff
ISM: Mfg: Prices Index (NSA, 50+ = Econ Expand)	level
CPI-U: All Items (SA, 1982-84=100)	log 1st diff
Mfrs' New Orders:Durable Goods Industries With Unfilled Orders (SA,Mil$)	log 1st diff
Manufacturers' New Orders (SA, Mil.$)	log 1st diff
Manufacturers' New Orders: Nondurable Goods Industries (SA, Mil.$)	log 1st diff
Mfrs' New Orders:Nondurable Goods Industries W/Unfilled Orders (SA,Mil$)	log 1st diff
Manufacturers' Unfilled Orders: Durable Goods Industries (EOP,SA,Mil.$)	log 1st diff
Manufacturers' Unfilled Orders (EOP, SA, Mil.$)	log 1st diff
Manufacturers' Unfilled Orders:Nondurable Goods Industries (EOP,SA,Mil$)	log 1st diff
Foreign Exchange Rate: Canada (C$/US$)	log 1st diff
Foreign Exchange Rate: Germany (D. Mark/US$)	log 1st diff
Foreign Exchange Rate: Japan (Yen/US$)	log 1st diff
Foreign Exchange Rate: Switzerland (Franc/US$)	log 1st diff
Contracts & Orders: Plant & Equipment (SA, Mil.$)	log 1st diff

Panel B: Quarterly Data

Data Description	Transformation
Business Sector: Compensation per Hour of all Persons (SA,1992=100)	log 1st diff
Business Sector: Real Compensation per Hour of all Persons (SA,1992=100)	log 1st diff
Business Sector: Unit Labor Costs (SA,1992=100)	log 1st diff
Business Sector: Unit Non-Labor Payments (SA,1992=100)	log 1st diff
Non-farm Business Sector: Unit Non-Labor Payments (SA,1992=100)	log 1st diff
Non-financial Corporations: Output per Hour, All employees (SA, 1992=100)	log 1st diff
Non-financial Corporations: Compensation per Hour, All employees (SA, 1992=100)	log 1st diff
Non-financial Corporations: Real Compensation per Hour, All employees (SA, 1992=100)	log 1st diff
Non-financial Corporations: Unit Labor Costs, All employees (SA, 1992=100)	log 1st diff
Non-financial Corporations: Unit Non-Labor Costs, All employees (SA, 1992=100)	log 1st diff
Non-financial Corporations: Total Unit Costs, All employees (SA, 1992=100)	log 1st diff
Business Sector: Real Unit Labor Costs (SA,1992=100)	log 1st diff
Non-financial Corporations: Real Unit Labor Costs, All employees (SA, 1992=100)	log 1st diff
Business Sector: Real Unit Non-Labor Payments (SA,1992=100)	log 1st diff
Non-farm Business Sector: Real Unit Non-Labor Payments (SA,1992=100)	log 1st diff
Non-financial Corporations: Real Unit Non-Labor Costs, All employees (SA, 1992=100)	log 1st diff
Non-financial Corporations: Real Total Unit Costs, All employees (SA, 1992=100)	log 1st diff
Government Total Receipts (SAAR, Bil. $)	log 1st diff
Government Total Expenditures (SAAR, Bil. $)	log 1st diff
Government Net Lending or Net Borrowing (SAAR, Bil. $)	1st diff
GDP Deflator	log 1st diff
Gross Private Domestic Investment: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Private Fixed Investment: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Private Non-residential Fixed Investment: Implicit Price Deflator (SA, 2000=100)	log 1st diff

Private Non-residential Structures: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Private Non-residential Equipment/Software: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Private Residential Investment: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Government Consumption/Gross Investment: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Federal Non-Defense Consumption/Investment: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Imports of Goods & Services: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Exports of Goods & Services: Implicit Price Deflator (SA, 2000=100)	log 1st diff
Non-farm Business Sector: Output per Hour of all Persons (SA,1992=100)	log 1st diff
Non-farm Business Sector: Compensation per Hour of all Persons (SA,1992=100)	log 1st diff
Non-farm Business Sector: Real Compensation per Hour of all Persons (SA,1992=100)	log 1st diff
Non-farm Business Sector: Unit Labor Costs (SA,1992=100)	log 1st diff
Non-farm Business Sector: Real Unit Labor Costs (SA,1992=100)	log 1st diff

Figure 1: Long Horizon Responses

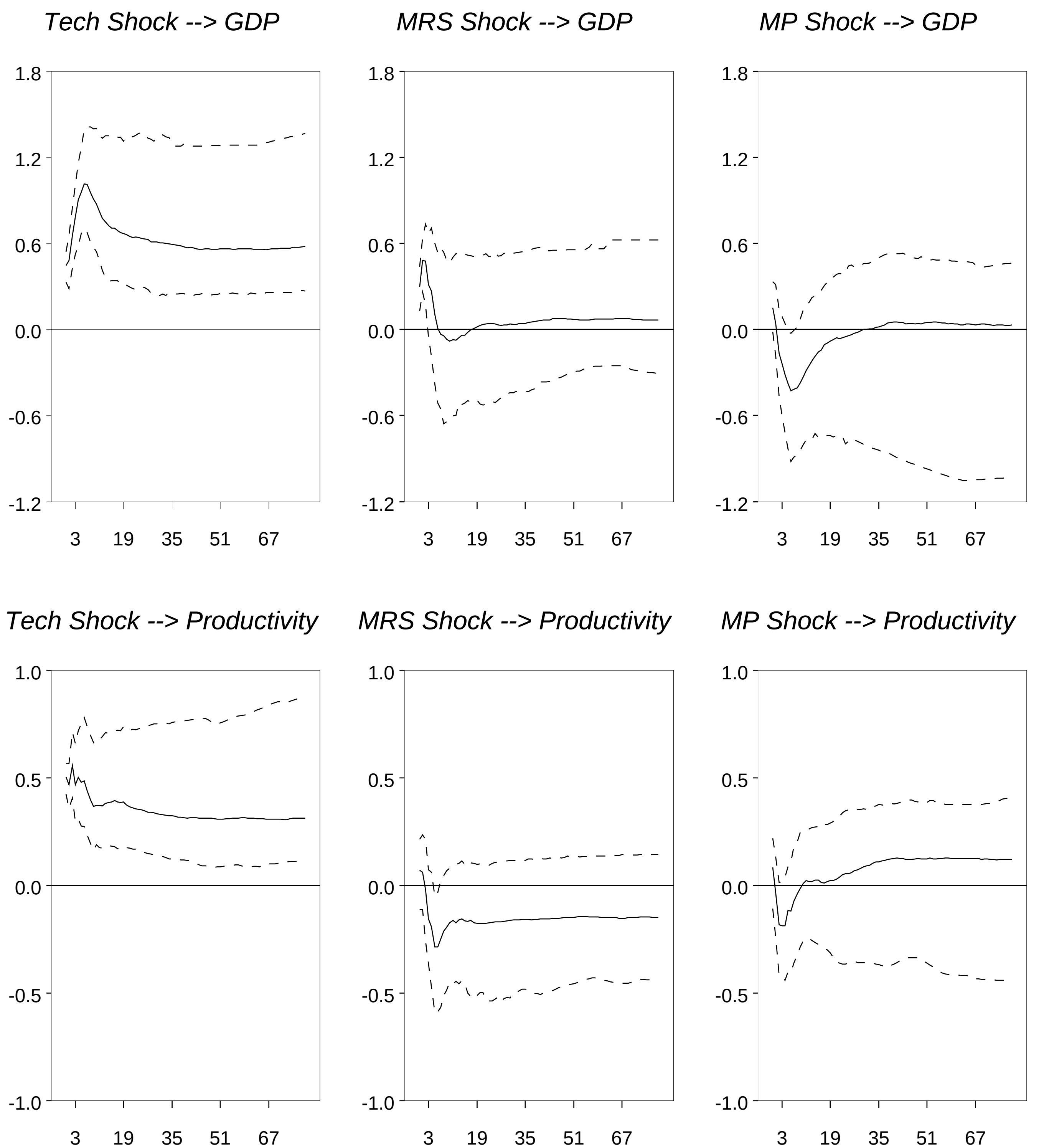

Figure 2: Cyclical Responses

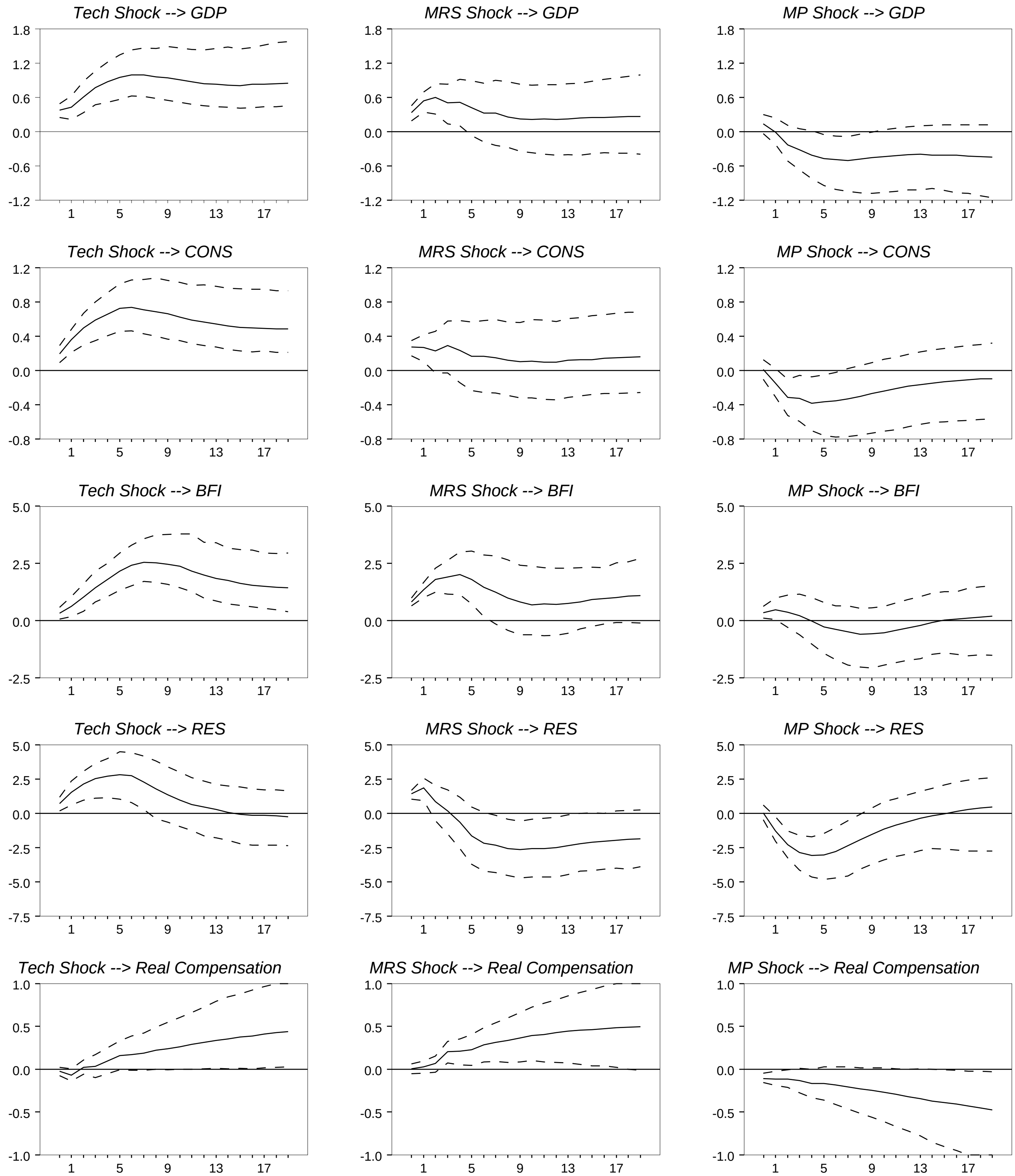

Figure 3: Responses of Labor Inputs and Productivity

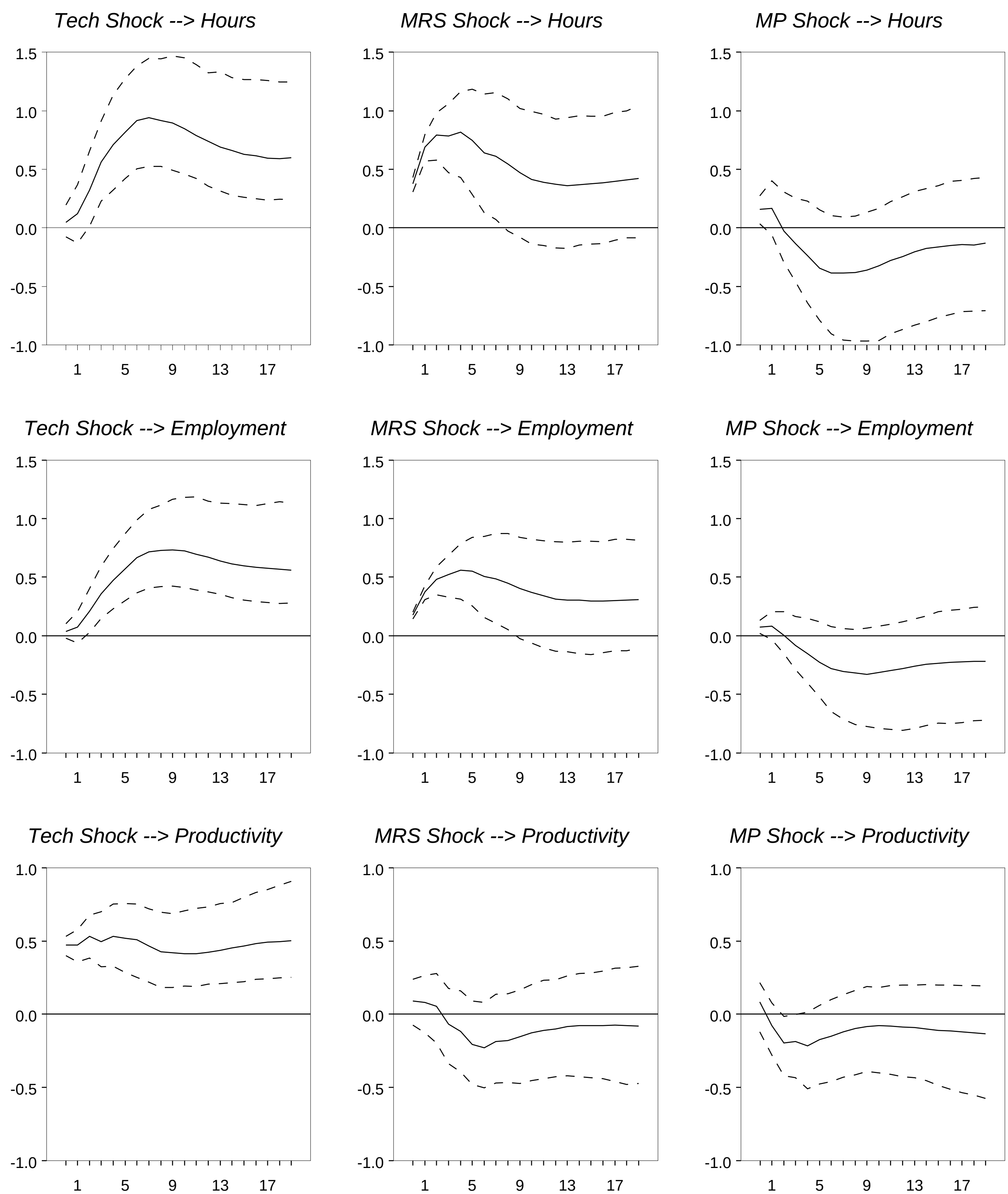

Figure 4: Responses of Inflation and Output Gap

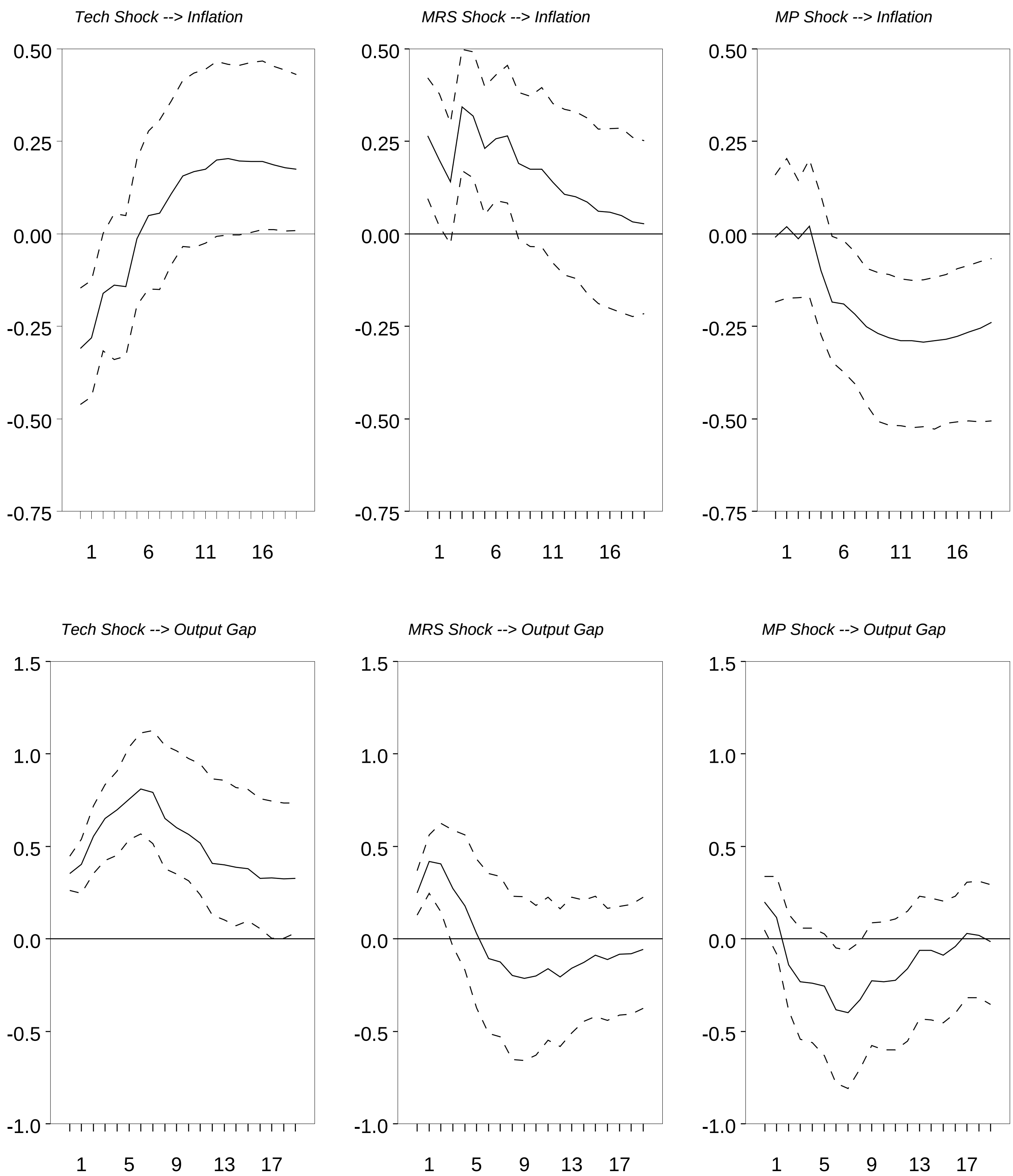

Figure 5: Responses of Interest Rates

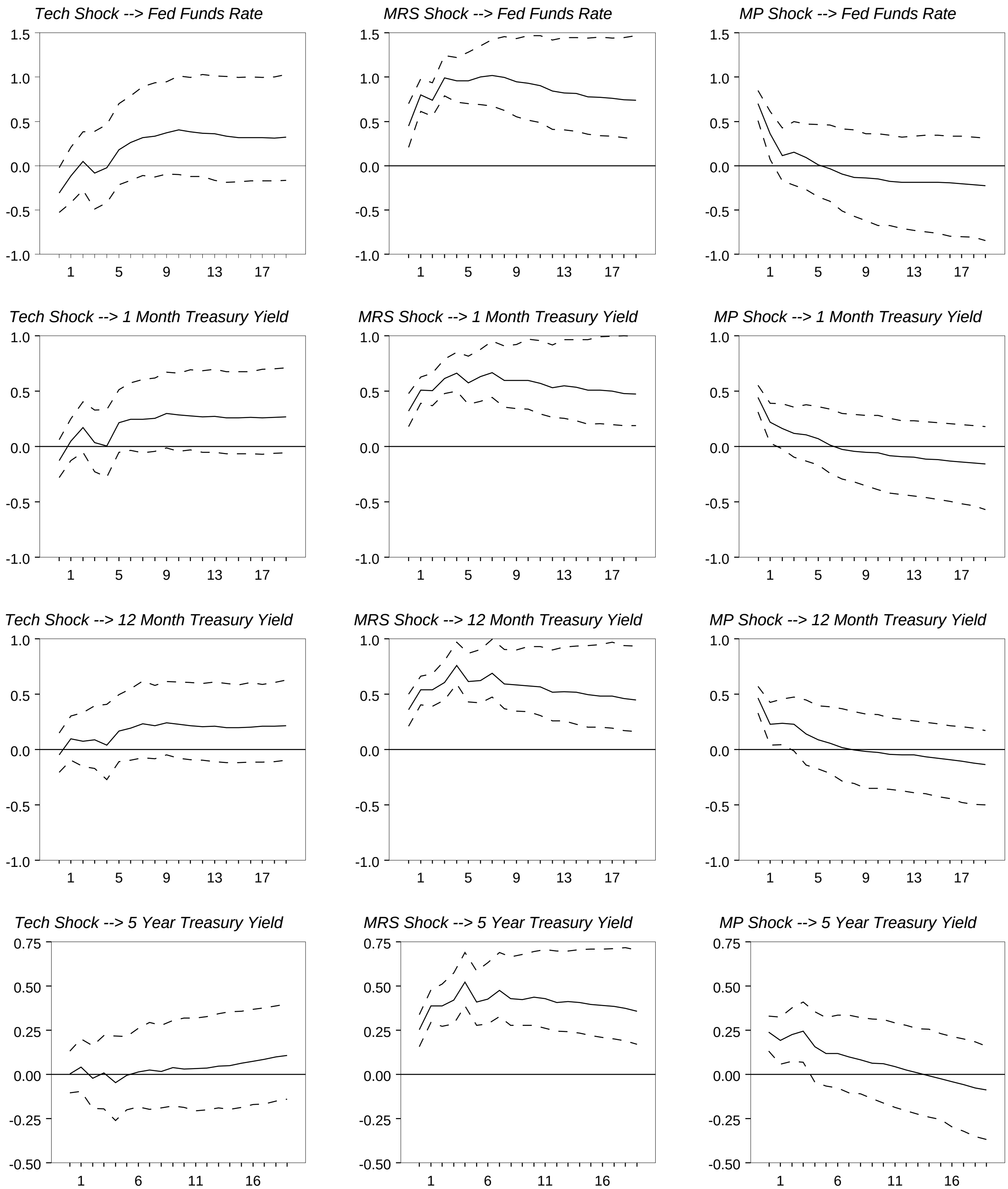

Figure 6: Responses of Equity Markets

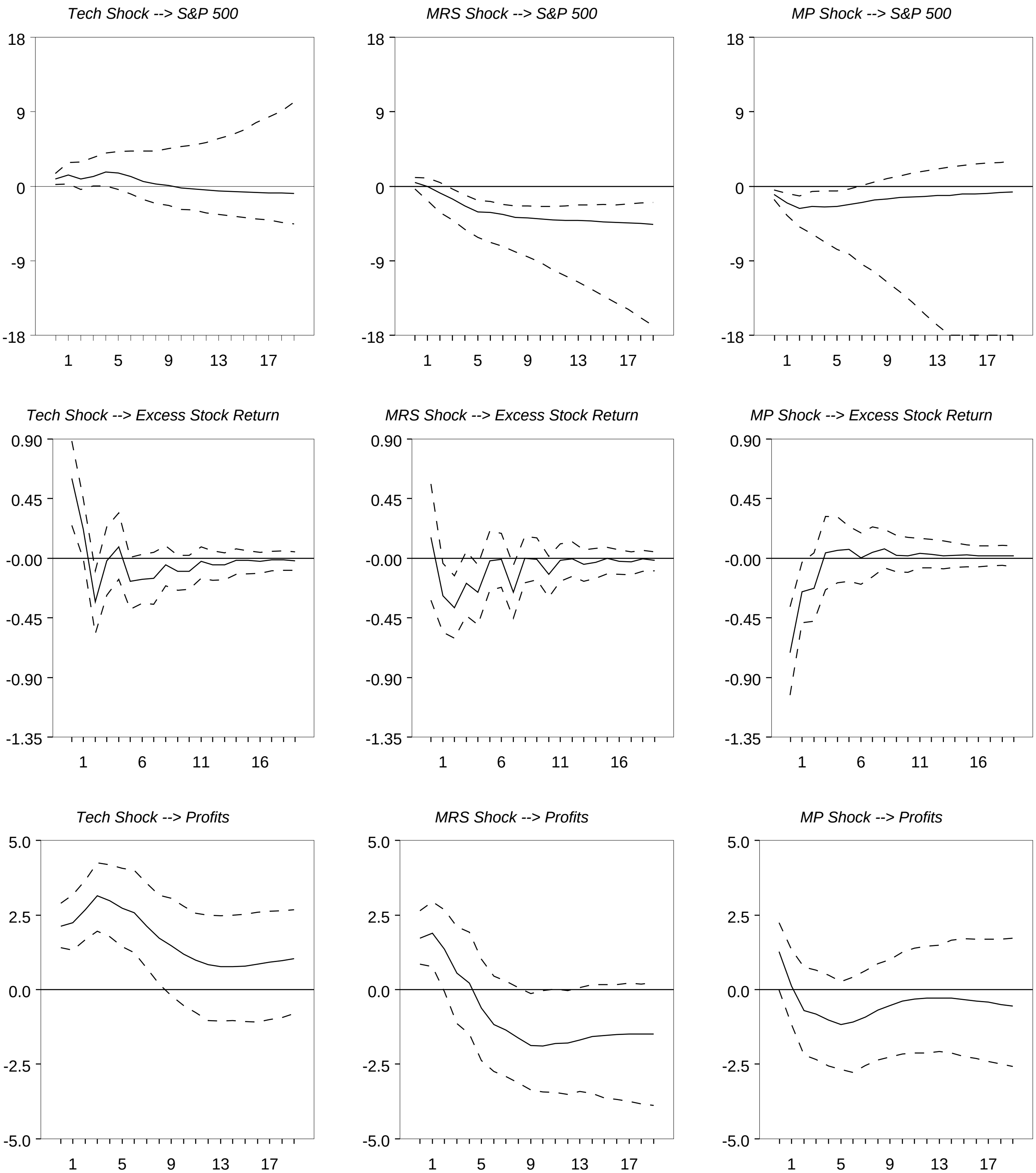

Figure 7

Baseline Shocks vs. Single-Eta Shocks