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Resumen

En el último tiempo, se ha observado un renovado interés en evaluar modelos económicos en un contexto de choques económicos específicos identificados empíricamente. Por lo general estos choques se identifican uno por uno, pasando por alto las posibles correlaciones entre ellos, o se identifican en el contexto de un vector autorregresivo estructural (SVAR) usando restricciones sólo débilmente relacionadas con la teoría económica. En este artículo desarrollamos un enfoque alternativo que utiliza medidas de choques económicos derivados explícitamente de modelos económicos para identificar múltiples impulsos estructurales ortogonales. Con este enfoque identificamos choques tecnológicos, de tasa marginal de sustitución (oferta laboral) y de política monetaria en el contexto de un FAVAR. Luego examinamos la distribución bayesiana posterior para las respuestas de un número alto de variables macroeconómicas y financieras endógenas a estos tres choques. Los choques dan cuenta de la preponderancia de las fluctuaciones de actividad, productividad y precios. Los choques tecnológicos tienen un impacto permanente sobre las medidas de actividad económica, en tanto los otros choques son más transitorios. Los insumos laborales tienen una respuesta inicial pequeña a los choques tecnológicos, y la respuesta va aumentando en forma consistente sobre un período de cinco años. La lenta respuesta del consumo al choque tecnológico es incoherente con una formulación simple de la hipótesis del ingreso permanente, pero sería coherente con un modelo de formación de hábitos. La política monetaria tiene una respuesta más bien pequeña al choque tecnológico, pero tiene una reacción contracíclica frente al más cíclico choque de oferta laboral. Este choque más cíclico tiene el impacto más fuerte sobre las tasas de interés. Los precios de las acciones responden a los tres tipos de perturbación. También se revisan varias otras implicancias empíricas de nuestro enfoque.

Abstract

Recently there has been renewed interest in assessing economic models in the context of specific, empirically identified economic shocks. Typically, these shocks are identified one-at-a-time, ignoring potential correlations across shocks, or are identified in the context of a structural vector autoregression (SVAR) using zero restrictions only loosely tied to economic theory. In this paper, we develop an alternative approach that utilizes measures of economic shocks explicitly derived from economic models to identify multiple orthogonal structural impulses. 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. We then examine the Bayesian posterior distribution for the responses of a large number of endogenous macroeconomic and financial variables to these three shocks.. The shocks account for the preponderance of output, productivity and price fluctuations. Technology shocks have a permanent impact on measures of economic activity, whereas the other shocks are more transitory. Labor inputs have little initial response to technology shocks, with the response building steadily over the 5 year period. Consumption's sluggish response to the technology shock is inconsistent with a simple formulation of the permanent income hypothesis, but would be consistent with a model of habit formation. Monetary policy has a rather small response to technology shocks, but responds "leans against the wind" in response to the more cyclical labor supply shock. This more cyclical 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

Recently there has been renewed interest in assessing economic models in the context of specific, empirically identified economic shocks. In recent examples Christiano, Eichenbaum and Evans (2005) and Altig, Christiano, Eichenbaum, and Linde (2004) assess Calvo-style models of nominal rigidities with respect to identified monetary policy and technology shocks. An earlier example is Rotemberg and Woodford (1997). In a related but somewhat different context, Chari, Kehoe and McGrattan (2002) find that "wedges" from the consumption-leisure Euler equation studied by Hall (1997) and Eichenbaum, Hansen and Singleton (1988) account for substantial variation in neoclassical business cycle models. While much progress has already been made in refining macroeconomic theories, our ability to assess alternative economic models on this basis and address critical macroeconomic questions depends on the quality and robustness of the identified economic shocks. This paper uses a relatively new and unexplored method for identifying economic shocks to address some of these issues.

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 vector autoregresssion (VAR). Although much has been learned through these methods, these 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).

Our empirical method is closest to Chari, Kehoe and McGrattan (2002) and Hall (1997). We identify economic shocks with specific stochastic driving forces measured from parameterized economic models drawn from the antecedent literature. In particular, we measure a shock to the marginal rate of substitution (MRS) between consumption and leisure using a procedure similar to Hall (1997). As Hall notes, this shock can be interpreted as a labor supply shock. It is similar to Chari, Kehoe and McGrattan's (2002) "labor wedge". We also measure technology shocks as particular Solow residuals and monetary policy shocks from a Taylor rule specification. At this point, our procedure deviates from Chari, Kehoe and McGrattan (2002). Since the three shock measures 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 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 restrictions used in VAR analysis. However, we do not impose all of the restrictions implied by economic models. In particular, 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 could offer a different perspective on economic issues of interest.

Evans and Marshall (2003) used a variant of this method previously 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). Finally, we expand the focus from interest rate responses to 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. For example:

- Can a small number of shocks account for most of 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, 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 ("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)

- How sticky are wages with respect to shocks that affect the marginal product of labor and the price level?

- What is the role of monetary policy in aggregate fluctuations? Is monetary policy largely driven 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 or "demand" shocks? Are monetary policy shocks an important fraction 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 for real side impulses (such as Phillips curve effects or shocks to marginal costs)?

- To what extent are movements in asset prices driven 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? To what extent can the three factors proposed by Fama and French (1993,1996) be interpreted as proxies for these macro impulses?

Our results shed light on all of 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 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-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 that boost labor's marginal product, with a monotonic rise 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 asset 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 the Bayesian approach to statistical inference we use.

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 seek to 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

$$E\varepsilon_t \varepsilon_t' = I \tag{1}$$

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

$$\eta_t = D_0\varepsilon_t + D_1\varepsilon_{t-1} + ... + D_K\varepsilon_{t-K} + \ w_t \tag{2}$$

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

$$E\varepsilon_t w_{t-j} = 0, \forall j = 0, \pm 1, \pm 2, ... \tag{3}$$

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 of only its own fundamental shock $\varepsilon_{i,t}$ (plus measurement error). However, if the i^{th} row of D_0 is non-diagonal, then the innovation to $\eta_{i,t}$ 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:

$$AY_t = \widehat{B}(L)Y_{t-1} + \begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix} \tag{4}$$

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,

$$E\left[\begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix}\begin{pmatrix} \varepsilon_t' & \gamma_t' \end{pmatrix}\right] = I \tag{5}$$

In the general case, representation (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 (4) can be written as a VAR:

$$Y_t = B(L)Y_{t-1} + u_t \tag{6}$$

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

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

and

$$\begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix} = Au_t \tag{7}$$

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

$$\varepsilon_t = A_\varepsilon u_t \tag{8}$$

so, combining equations (2) and (8), we get

$$\eta_t = C_0 u_t + C_1 u_{t-1} + ... + C_K u_{t-K} + w_t \tag{9}$$

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

$$C_k \equiv D_k A_\varepsilon, k = 1, ..., K \tag{10}$$

Equations (1) and (8) imply

$$I = A_\varepsilon \Sigma_u A_\varepsilon' \tag{11}$$

2.2 Identification

Note that equations (10) and (11) imply

$$D_0 D_0' = C_0 \Sigma_u C_0' \tag{12}$$

Equation (12) 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 data. We then impose additional assumptions to ensure that the decomposition in equation (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:

$$E\gamma_t w_t = 0 \tag{13}$$

Together, equations (3), (7), and (13) ensure that $Eu_t w_t' = 0$, so we can estimate $C_k, k = 0, ..., K$ by regressing η_t on u_t.

While equation (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 (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:

$$\begin{aligned} d\,(D_0) &= \tilde{d} \\ D_0 D_0' &= C_0 \Sigma_u C_0' \end{aligned} \tag{14}$$

For example, one possible set of identifying restrictions could be that the D_0 matrix be lower-triangular.[1] These restrictions would be represented by system (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. Having identified D_0, we can then identify A_ε using equation (10), and we can identify ε_t using equation (8).

To compute impulse responses of Y_t to ε_t, rewrite the reduced form (6) as

$$Y_t = B(L)Y_{t-1} + A^{-1} \begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix}. \tag{15}$$

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

$$\left[A^{-1}\right]_\varepsilon = \Sigma_u A_\varepsilon' \tag{16}$$

which follows directly from equation (11).

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

Once $\left[A^{-1}\right]_{\varepsilon}$ 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 (6) and (7) with another equation in z_t:

$$\left[\begin{array}{c} Y_t \\ z_t \end{array}\right] = \left[\begin{array}{cc} B(L) & \mathbf{0} \\ \phi(L) & \theta(L) \end{array}\right] \left[\begin{array}{c} Y_{t-1} \\ z_{t-1} \end{array}\right] + \left[\begin{array}{cc} A^{-1} & 0 \\ F & G \end{array}\right] \left[\begin{array}{c} \left(\begin{array}{c} \varepsilon_t \\ \gamma_t \end{array}\right) \\ \nu_t \end{array}\right]. \tag{17}$$

In equation (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 (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.[2]

To address this problem, we follow Bernanke Boivin, and Eliasz (2005) and implement equation (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:

$$X_t = \Lambda \widehat{Y}_t + e_t. \tag{18}$$

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 (4) in place of Y_t.

Note that this is a two-step procedure: first we estimate equation (18) to generate $\widehat{Y}_t$, and then we estimate equation (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.[3]

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

[3] There is a technical issue in using $\widehat{Y}_t$ in place of Y_t in equation (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

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 in 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 (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.[4] An alternative procedure would be to impose a prior on parameter matrices $\{\Lambda, \Sigma_\nu\}$ in equation (18), and then compute the joint posterior over all the parameters. Given the large size of these matrices, we have elected not to do so.[5]

Note that the parameter vector $\tilde{d}$ differs from the other parameters. Since exactly $m(m-1)/2$ 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 more 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. Thus far, we have only explored the implications of this uninformative prior. It would be 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 in 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.

(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 (17) as a maintained assumption

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

[5] In our empirical application, Λ is 190×6 and Σ_ν, the covariance matrix of ν_t, is 190×190.

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 residual measures is endogenous, responding to macro shocks.[6] 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:

$$\begin{aligned} Y_t &= z_t \; g_t F(v_t K_t, e_t N_t) \\ \ln z_t &= \mu + \ln z_{t-1} + \varepsilon_{Tech,t} \end{aligned} \tag{19}$$

where Y, z, v, K, e, and N are the levels of output, technology, capital utilization rate, capital stock, labor effort, and labor hours.[7] 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 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.

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 ε_{Tech}.[8] 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 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.[9] Consider a representative consumer with the following utility specification that includes external habit persistence

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

[6] For example, see Burnside, Eichenbaum and Rebelo (1993) and Braun and Evans (1998).
[7] Throughout this paper, we omit the time subscript t if no ambiguity is implied.
[8] We thank John Fernald for providing us with this time series on technology shocks.
[9] Holland and Scott (1998) study a similar MRS shock for the United Kingdom economy.

$$\ln \xi_t = \rho(L) \ln \xi_{t-1} + \varepsilon_{MRS,t} \tag{20}$$

where C is consumption of the representative agent, $\overline{C}$ represents the per-capita aggregate consumption level, N is labor hours, ξ is a serially correlated preference shifter, and ε_{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)

$$\frac{\xi_t \left(C_t - b\overline{C}_{t-1}\right)^{-\gamma}}{N_t^{\phi}} = \frac{1}{W_t \left(1 - \tau_t\right)} \tag{21}$$

where W_t is the real wage and τ_t is the labor tax rate. Taking logs, one obtains

$$ln\ \xi_t = \phi\ ln\ N_t - lnW_t - \ln\left(1 - \tau_t\right) + \gamma ln\left[C_t - b\overline{C}_{t-1}\right]. \tag{22}$$

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

We use equation (22) 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 (20). Our data are quarterly and extend from 1964:I to 2000:IV. Consumption is measured by per capita non-durables 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).[10] The utility function parameters are taken from previous studies. 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 (20). 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 measurement errors in ξ_t, we use an instrumental variables estimator to estimate $\rho(L)$.[11]

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

[11] 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.

Many macroeconomic researchers have recently offered several differing interpretations for the random marginal rate of substitution shifter ξ_t in equation (21).[12] First, the home production literature due to Benhabib, Rogerson, and Wright (1991) and Greenwood and Hercowitz (1991), 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 (21). In particular, in the Calvo pricing environments considered by Christiano, Eichenbaum, and Evans (2005) and Galí, Gertler, Lopez-Salido (2001), alternative versions of (21) hold. Third, Chari, Kehoe, and McGrattan (2003) and Mulligan (2002) interpret ξ_t as reflecting wedges or 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 potential). In some specifications, lags of the short-term interest rate are included, in order to capture a desire of the monetary authority to smooth changes in the interest rate.[13] 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 ε_{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.[14] In addition, we allow the coefficients on

[12] 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.

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

[14] 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

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:

$$rff_t = \sum_{j=1}^{4} \alpha_j rff_{t-j} + \sum_{k=1}^{3} \left[\beta_k \left(I_k ugap_t\right) + \delta_k \left(I_k \pi_t\right)\right] + \eta_{MP,t} \tag{23}$$

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,[15] 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 Properties of the Model-Based Shocks

In this section we explore the statistical properties of the model-based shock measures. Table 1 displays the contemporaneous correlation matrix for η_t. These non-zero correlations, while not large, contradict the usual assumption in the structural VAR literature that the fundamental shocks be mutually uncorrelated.

Exogenous shocks ought to be causally prior to any endogenous variables. While we do not use the model-based measures η_t directly as the structural shocks, clearly causal priority is a desirable characteristic for our η_t measures. Gali, Gertler, and Lopez-Salido (2001) specifically raised 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. To investigate this issue for our vector of model-based shocks, we conduct a series of tests similar to those used by Gali, Gertler, and Lopez-Salido (2001). In particular, we estimate two sets of forecasting regressions for each measure:

$$\eta_{i,t} = \sum_{j=1}^{N} \beta_j \chi_{t-j} + w_{i,t}.$$

and

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

Here, $i = \{MP, MRS, TECH\}$, and χ_t denotes a candidate explanatory variable. Following Gali, Gertler, and Lopez-Salido (2001), we use detrended GDP, the federal funds rate, and the term spread as possible χ_t series, included one at a time in each regression.

The exclusion test for the first regression asks whether each of the three endogenous predictors are useful in forecasting the η_t measures. The test for

use the Staiger-Stock-Watson gap measure.

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

the second regression is a conventional Granger causality test. We perform both tests because we found that the Granger causality tests are very sensitive to sample period. The results are displayed in Table 2

The implications of the first regression (labelled "Forecast" in the table) give no evidence of endogeneity for η_{MRS} and little evidence for η_{MP}. There is some evidence that detrended GDP can forecast η_{TECH}. The Granger causality tests confirm exogeneity of η_{MRS}, but paint a rather different picture for η_{MP}. These discrepancies appear to involve small sample issues, so we are uncertain how much credence to give these results.[16] It is noteworthy that there is essentially no evidence against exogeneity of our MRS shock, even though this measure was the focus of Gali, Gertler, and Lopez-Salido's (2001) critique.

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) and (1) imply that

$$var_{t-1}\left(\eta_{i,t} - w_{i,t}\right) = \sum_{j=1}^{m} D_{0,ij}^2 \tag{24}$$

where $D_{0,ij} = (i,j)^{th}$ element of matrix D. We will refer to the left-hand side of equation (24) as the "non-noise variance" of $\eta_{i,t}$. So to ensure that most of this variance is driven by the own shock ε_i, we need for 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

$$\frac{D_0,_{ii}^2}{\sum_{j=1}^{m} D_0,_{ij}^2} = \tilde{d}_i,\ i = 1,2,3$$

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 our model-based measures η_i is due to its own shock ε_i.[17]

[16] Note especially the apparent evidence of Granger causality of η_{MP} by the fed funds rate, where the marginal significance level is 0.005 when four lags are used. According to equation (23), η_{MP} is orthogonal to four lags of the funds rate, so the marginal significance of this exclusion test must be 1.0 in population.

[17] An alternative approach to identifying D_0 would be simply to choose the elements of D_0 to maximize $\sum_{i=1}^{3} \tilde{d}_i$ subject to constraints (12). In other words, choose the D_0 matrix so that the average fraction of "non-noise variance" of η_i accounted for by its own shock ε_i is maximized. The problem with this approach is that the constraint set implied by constraints

4.3 FAVAR Specification

In order to ensure that our information set X_t in equation (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 2004:Q4. The data series used are listed in the Data Appendix, along with the transformations used to induce stationarity.[18] We then compute $\widehat{Y}_t$ in equation (18) as the first six principal components of X_t. (That is, we set n = 6.)[19] Four quarterly lags of each principal component are used in the VAR, equation (4). We then use equation (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 for the data we use. It displays the R^2s for the *OLS* regressions in system (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 rejects these hypotheses at any desired significance level. Under our identifying restrictions, these statistics imply that these measures are potentially informative for the true structural shock vector ε_t.

5 Empirical Results

Our empirical results are displayed in Table 4 and Figures 1-3. For each of the twenty-four endogenous variables listed, the table 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

(12) is non-compact. To see this, note that the unconstrained maximum of $\sum_{i=1}^{3} \tilde{d}_i$ is attained by setting $\tilde{d}_i = 1, \forall i$. That is, set all non-diagonal elements of D_0 to zero. Of course, this generically violates constraints (12) (unless $C_0 \Sigma_u C_0'$ happens to be diagonal). But setting $\tilde{d}_i = 1 - \varepsilon$ for some very small $\varepsilon > 0$ generally does *not* violate the constraints. One generally can find a D_0 matrix satisfying equation (12) for which $\tilde{d}_i = 1 - \varepsilon, \forall i$. Given this non-compact constraint set, there is no guarantee that the constrained maximization problem proposed in the beginning of this footnote can be solved. In practice, we were unable to find a constrained maximum for our estimated value of $C_0 \Sigma_u C_0'$.

[18] 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.

[19] 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.

following each median statistic give the 95% and 5% quantiles of the posterior distribution for each forecast variance fraction. The subsequent figures display the median impulse responses of these endogenous variables (solid lines) over a 20-quarter horizon. 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 Explanatory Power of the Identified Shocks

A general conclusion one can obtain from the variance decompositions in Table 4 is that our identified shocks $\{\varepsilon_{MP}, \varepsilon_{MRS}, \varepsilon_{TECH}\}$ collectively give a fairly comprehensive picture of the behavior of key macroeconomic and (to a lesser extent) financial variables, although there is certainly a good deal of variability that is due to other sources. First note that most of the short-run variance in economic activity is explained by these three shocks. In particular, 72% of three-month-ahead variance of output explained by these shocks (at the median of the posterior distribution). This fraction rises to 84% at the five-year horizon. Recall that there are a total of six VAR innovations, so there are three remaining sources of variation (the γ_t vector) in system (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 three-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.

The reason that the technology shock dominates output variation at long horizons is that it is by far the most persistent shock. The impulse responses, displayed in Figure 1, show that the effect of ε_{TECH} appears to be permanent, in that there is no evidence of any reversion of output to its pre-shock level even after 5 years. In contrast, Figure 2 shows that the response of output to ε_{MRS}, while large during the first two years, reverts back towards zero thereafter. (According to the posterior distribution, there is a 24% probability that the average response in the third year is negative. The corresponding probability for the technology shock is zero, to three significant digits.) Thus, while technology shocks have a quasi-permanent impact on output, the MRS shock appears more cyclical. So, we're finding something like a permanent vs transitory decomposition without imposing it as an indentifying restriction.[20]

The three shocks identified here also appear to drive a good deal of the variation in prices, although not quite as much as for real economic activity. In particular, while the median of the posterior distribution implies that only

[20] The permanent vs. transitory decomposition is used as an *a priori* identifying restriction in Blanchard and Quah (1989), Gali (1992, 1999), and Christiano, Eichenbaum, and Vigfuson (2003, among others.

about 20% of short-run inflation variability is driven by the three shocks, these shocks account for fully 60% of the five-year ahead inflation variance. At this longer horizon, all three shocks appear to be important, with the monetary policy shock first among (approximate) equals.

Fluctuations in labor productivity are driven mostly by technology shocks. However, the MRS shock is the dominant source of short- to medium-run variation in labor input variables, such as payroll employment and hours worked. Perhaps this is no surprise, given that this shock can be interpreted as a labor supply shock.

Measures of fixed investment have a somewhat smaller fraction of short-run variance explained by the three shocks we identify, but the explanatory power of the shocks for longer-run investment variation is high. In particular, investment in equipment/software, structures, and residential housing all have 40% or less of the near-term variation explained by the three shocks. However, the three shocks explain a much larger fraction of the longer-run investment variance. They account for over 60% of the five-year ahead variance of these fixed investment series. For all these measures, the cyclical ε_{MRS} shock tends to play the strongest role of the three shocks.

Consumption and housing expenditure is also reasonably well explained by the three identified shocks. In particular, between 50% and 62% of the five-year ahead variation of these measures is explained by the shocks (at the median). The MRS shock tends to be the most important for short-term variability, while the more permanent technology shock is most important for explaining long-run variability.

Of the three identified shocks, the most important near-term driver of monetary policy is the monetary policy shocks: the median fraction of the federal funds rate's one-quarter ahead forecast error accounted for by ε_{MP} is 34%. Longer term variation in the funds rate, however, increasingly represents endogenous responses of the Fed to non-policy shocks, especially the MRS shock. In particular, the Fed seems to "lean against the wind" (after 3 or 4 quarters) in response to an expansionary realization of ε_{MRS}. As a result, the preponderance of 5-year ahead variation in the federal funds rate is accounted for by the MRS shock.

Turning to financial markets, we find that our three shocks explain a median value of between 66% and 75% of the five-year ahead variability in Treasury yields. As in Evans and Marshall (2003), the primary driver of these yield variations is the MRS shock. In addition, a not-inconsiderable fraction of stock market variability can also be accounted for by these macro shocks. At the median of the posterior distribution, we find that 26% of the five-year ahead forecast error for the change in the S&P500 index can be accounted for by these shocks. In contrast, at the three-month horizon stock price variation appears to be largely de-linked from macroeconomic factors. The three shocks are about equally important as drivers of stock market returns. A somewhat larger fraction of exchange rate variability is accounted for by these shocks. Our 3 shocks drive a median of 41% of the 5-year ahead variation in the pound/dollar exchange rate.

5.2 Results from Impulse Responses

5.2.1 Responses of Real Economic Activity to Technology Shocks

As mentioned above, many indicators of real economic activity have permanent responses to ε_{TECH}, our measure of the technology shock. GDP and labor productivity shoot up initially, and remain high throughout the 5 year period for which we plot responses. In contrast, measures of labor inputs have little initial response, but build steadily over the 5 year period. This can be seen in measures of employment and hours. A number of papers have studied the response of employment and hours to a technology shock. Some, like Basu, Fernald, and Kimball (2005), argue that technology shocks are contractionary for labor markets, as firms respond to productivity innovations by cutting hours. Others, like Christiano, Eichenbaum, and Vigfuson (2003) find an immediate response of hours. Our results are mid-way between these two camps. They suggest that labor markets have essentially no responses initially to a technology shock. The response builds over the following 5 years.[21]

Both the impulse responses in Figure 1 and the variance decompositions in Table 4 imply that the technology shock is a key driver of procyclical labor productivity. The probability that this response is positive over the first year is virtually 100%. In contrast, the responses of productivity to the MRS and monetary policy shocks (displayed in Figures 2 and 3) are small and dissipate quickly. We would tentatively associate the "labor hoarding" explanation for procyclical productivity with a positive productivity response to the MRS shock (interpreted as an aggregate demand shock). The small responses of productivity to ε_{MRS} provides little evidence of this.

The real wage rises with technology shocks, but the effect is virtually invisible over the first year. After the first four quarters, however, the wage starts to rise, with a steady increase over the next 5 years. If the real wage equalled the marginal product of labor, it would mimic the response of productivity. However, average productivity (which would be proportional to the marginal productivity with Cobb-Douglas technology) rises by 0.49% in the four quarters following a one-standard-deviation technology shock, while the response of the real wage is negligible. We see a similar non-response of the real wage on impact to ε_{MRS}. Noting that both ε_{TECH} and ε_{MRS} elicit strong responses of inflation (as we shall discuss below), these results suggest substantial stickiness in the *real* wage process, rather than the sort of nominal wage stickiness modeled by Erceg, Henderson, and Levin (2000) and Christiano, Eichenbaum, and Evans (2005).

Fixed investment variables (investment in equipment and software, and both residential and nonresidential structures) respond strongly to technology shocks, although with a lag. In each case, the initial response is small, but the response builds steadily over the next two years. A similar response pattern

[21] Christiano, Eichenbaum, and Vigfuson (2003) find that technology shocks appear contractionary for labor input when the VAR used to identify the shocks is specified in log first differences, while a positive response on inpact is associated with VARs specified in log levels. Our VAR is specified in log levels,and we obtain an intermediate result.

obtains for an expansionary MRS shock (with the exception of residential structures), suggesting that this "hump-shaped" response is due to adjustment costs in investment, rather than something specific about the technology shock.

The permanent response of wages and payrolls to a technology shock implies that this shock induces a pronounced increase in permanent income. Thus, it is noteworthy that consumption expenditure and its components all have rather small responses to the technology shock on impact. Thereafter, consumption continues to rise, mimicking the behavior of employment, hours, and the real wage. 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, 2002).

5.2.2 Responses of Inflation to Technology Shocks

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 (as long as the initial response of aggregate demand or monetary policy is not too big). According to a Taylor Rule, the appropriate monetary policy response would be to reduce short-term interest rates, since this shock decreases near-term inflationary expectations while increasing potential output. Our results do show substantial probability of such an expansionary response. In particular, the probability of a negative response of the federal funds rate over the first 4 quarters is 72%. After the first 6 quarters or so, however, inflation appears to rise, and monetary policy responds by contracting. What appears to be driving this inflation increase is the delayed response of consumption to the increase in permanent income, discussed above. The technology shock also induces an increase in productive capacity (both directly and as a result of the investment response). However, if the rise in demand exceeds the rise in capacity over the horizon displayed in the impulse responses, an output gap could appear, which would be associated with inflationary pressures. The increase in the federal funds rate at this point would be the appropriate policy response to this sort of development.

5.2.3 Responses of Financial Variables to Technology Shocks

The responses of nominal treasury yields to technology shocks are somewhat ambiguous. While the median responses are positive (except for a short-lived decline initially for the 1- and 12-month yields), the distribution is quite spread out. 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 in Evans and Marshall (2003),a technology shock moves real rates and expected inflation in opposite directions. These two components affect nominal yields in opposite directions, so the theoretical predictions for nominal yields' response to technology shocks is 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 approximately of the same magnitude, at least over the first year or so. As a result, the technology shock has a negligible initial effect on nominal yields. Thereafter, the dominant effect on the short-term yields is the longer-run positive response of inflation and the associated monetary policy contraction (described in the previous paragraph). These effects tend to push rates up.

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 are 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. (As we shall see in section 5.2.5, below, the stock market does appear to respond strongly to monetary policy.) These equity market responses can also be seen in the notable responses of the three Fama and French (1993, 1995) factors.[22] The first Fama-French factor (the excess return to the market) is essentially the derivative of the stock price level, initially displaying a strong rise and bouncing around thereafter. The small-stock factor also rises substantially, implying that small stocks respond more strongly to the technology shock than large stocks. (This may simply reflect the higher volatility of small stocks. Alternatively, small stocks may be more heavily weighted in the technology sector.) Finally, the book-to-market factor falls initially, and then rises for about three quarters. Fama and French (1995) tentatively interpret this book-to-market factor as a "distressed firm factor". This interpretation would be consistent with our results, since a time of rising productivity would presumably have a particularly salutary effect on firms that had been in distress, increasing their return relative to non-distressed firms. On the whole, these responses of equity valuations to an increase in factor productivity accords with our economic intuition, but we find it striking nonetheless that the effect comes through so clearly in this exercise.

5.2.4 Responses to MRS Shocks

Most measures of real economic activity display positive initial responses to ε_{MRS}. The clearly positive response lasts about one to two years. Thereafter, the declining response and widening distribution makes it difficult to assert a continued positive response. We can see this pattern in the responses of GDP,

[22] The three Fama-French factors are (1) the excess return to a diversified value-weighted portfolio; (2) the difference between the returns to a small-cap stock portfolio and a large-cap portfolio ("SMB"); and (3) the difference between the returns to a portfolio with a high book-to-market ratio and one with a low book-to-market ratio ("HML")

employment, hours, investment in equipment and software, and consumption. Both residential investment and housing starts rise initially, but then fall off quickly, perhaps in response to the increase in real interest rates, discussed below. The response of consumption and its components is positive, but more muted than investment and labor supply. In these respects, ε_{MRS} looks like a nonpersistent cyclical impulse.

Prices and inflation rise 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.

With both inflation and output rising, without a concomitant increase in potential output, 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 of the monetary authority is quite long-lived: the median funds rate remains about 70 basis points above its starting value even after five years. To our eyes this looks like a classic countercyclical response to a demand shock.

Interest rates of all maturities rise in response to ε_{MRS}. These increases are roughly parallel, inducing a pronounced rise in the level of the yield curve. Furthermore, these interest rate increases exceed the positive response of the inflation rate (cumulated over the appropriate horizons), so real interest rates display substantial, significant, and persistent increases.

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. Thus, this negative response of stock markets to an expansionary MRS shock looks like an instance of "good news is bad news": the expansionary shock increases cash flows by less than it increases future discount rates, decreasing stock prices.[23]

5.2.5 Monetary Policy Shocks

A contractionary monetary policy shock increases the fed funds rate by about 70 basis points on impact. This effect on the funds rate is quite transitory, dissipating in about 2 quarters. One also sees a rather short-lived response in other interest rates. The contractionary policy shock tends to reduce GDP after about a quarter. This decline in GDP is quite persistent. Its lack of mean reversion in response to a monetary policy shock could be construed as a violation of long run neutrality, although the distribution is rather spread out. However, other indicators of real economic activity do evidence substantial mean reversion after the initial negative response. In particular, we see this pattern in mea-

[23] See Boyd and Jagannathan (2004) for a discussion.

sures of labor inputs, consumption, and, most notably, in components of fixed investments. The negative response and subsequent snap-back of residential investment and housing starts is particularly strong.

The monetary policy contraction has little effect on the price level and inflation rate in the first few quarters. Thereafter, both prices and inflation display a prolonged fall, as one would expect from a monetary contraction. Thus, our measure of monetary policy shocks does not display the sort of "price puzzle" often found in other measures of policy shocks. (See, e.g., the discussion in Christiano, Eichenbaum, and Evans, 1999.).

Interestingly, our results indicate a substantial and fairly long-lived negative response of stock prices to a contractionary ε_{MP} shock. The response S&P500 index lasts at least two years. In particular, the median stock index response in the eight quarters following the shock is a decline of over 2 percent. The probability of a negative response over this period is over 98%. The excess return to the S&P 500 portfolio declines by about 70 basis points on impact with negative excess returns persisting for at least two quarters. The Fama-French small stock factor also declines over the first two quarters, implying a stronger response of small stocks to the monetary contraction. It is of interest that the Fama-French HML factor responds positively on impact and one quarter thereafter. In other words, growth stocks fall by more than value stocks in response to a monetary policy shock. All this conforms roughly to the conventional wisdom that monetary contraction is bad for the stock market.

The exchange rate value of the dollar vs. the British pound tends to react positively in response to a contractionary ε_{MP} shock. This is consistent with Eichenbaum and Evans (1995), and is in part a response to the positive response of interest rates.

5.3 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 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, one at a time. We call this the "single-η approach". This simpler approach ignores the correlations among the elements of η_t (documented in Table 1). It also ignores possible contamination of $\eta_{i,t}$ with $\varepsilon_{j,t}$, $j \neq i$, 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 baseline approach of section 2.

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

$$\begin{bmatrix} \eta_{i,t} \\ z_t \end{bmatrix} = \Phi(L) \begin{bmatrix} \eta_{i,t-1} \\ z_{t-1} \end{bmatrix} + \Sigma \upsilon_t, \quad E\upsilon_t \upsilon_t' = I \tag{25}$$

where $\eta_{i,t}$ is one of our three model-based shock measures and z_t is one of the endogenous variables whose responses we wish to explore (that is, one of the variables in Table 4), υ_t is a bivariate i.i.d. disturbance, and Σ is lower triangular. In this structure, $\upsilon_{1,t}$ is interpreted as the shock to $\eta_{i,t}$. We use four quarterly lags in this VAR.

While most of the responses to the model-based shock measures in framework (25) are qualitatively the same as in our baseline approach, there are a several differences worthy of note. First, and most notably, the inflation response to the shock to η_{MP} in framework (25) displays a huge price puzzle. As shown in Figure 4, a contractionary shock to η_{MP} (the "Taylor rule residual") 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 4).

Second, measures of consumption and investment appear to display permanent responses to η_{MP} in framework (25), which would appear to violate long run neutrality. Again, these differ from the response patterns to ε_{MP}. (Both are displayed in Figure 4.) Third, investment in nonresidential structures has a positive, significant, and long-lived response to a contractionary η_{MP} response. This is difficult to rationalize, given that the η_{MP} increases interest rates of all maturities while reducing economic activity.

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. Let us consider what we've learned from our approach about these issues.

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 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, however, 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).

Somewhat surprisingly, we find clear evidence of *real* (not nominal) wage stickiness. In particular, real wages hardly move on impact in response to the technology shock or the MRS shock, while inflation responds on impact to both of these shocks.

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 the 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 are 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 are driven by factors other than the macroeconomic factors 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), confirming the folk wisdom that the market sometimes treats good news as bad news.

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 is it a shock to implicit labor taxes or labor market frictions? Can the evidence of real (as opposed to nominal) wage stickiness be supported by disaggregated data? 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 useful first 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:[24]

$$p(C, \Sigma_w, B, \Sigma_u) = p(C|\Sigma_w, B, \Sigma_u)\, p(\Sigma_w|B, \Sigma_u)\, p(B|\Sigma_u)\, p(\Sigma_u) \qquad (26)$$

We assume uninformative priors in the usual way:

$$prior(\Sigma_u) \propto |\Sigma_u|^{-(n+1)/2} \qquad (27)$$

[24] All densities in equation (26) are conditional on the data $\{Y, X, H\}$. This dependency is not noted explicitly.

$$prior(B) = \text{constant} \tag{28}$$

$$prior\left(\Sigma_w\right) \propto \left|\Sigma_w\right|^{-(m+1)/2} \tag{29}$$

$$prior(C) = \text{constant} \tag{30}$$

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

$$Y = XB + U \tag{31}$$

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

$$u_t \sim N\left(0, \Sigma_u\right). \tag{32}$$

In equation (31), 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

$$\widehat{B} \equiv \left(X'X\right)^{-1} X'Y \tag{33}$$

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 $\widehat{B}_s$ denoted the vectors formed by stacking the columns of B and $\widehat{B}$, respectively.

Zellner (1971) shows that, given the priors (27) and (28), 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 (26). Equation (2) can be written

$$H = \widetilde{U}C + W. \tag{34}$$

In equation (34), $\widetilde{U}$ 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

$$W \sim N\left(0, \Sigma_w\right). \tag{35}$$

We follow the same steps as we used to derive $p\left(\Sigma_u\right)$ and $p\left(B|\Sigma_u\right)$, 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

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

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

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 (31) 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 (34) via OLS. $V(B)$ is the moment matrix of the residuals from this OLS estimation of equation (34). 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 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 $\Sigma_w \otimes \left(\widetilde{U}(B)'\widetilde{U}(B)\right)^{-1}$.

Data Appendix I

Monthly Data: 1967:01 - 2003:12

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
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

Data Appendix II:

Quarterly Data: 1967:1 - 2003:4

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

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Table 1: 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 2: Exogeneity of Shock Measures: Marginal Significance of Exclusion Tests for Forecasting and Granger Causality Regressions

Explanatory Variable	# Lags	MP Shock		MRS Shock		Tech Shock	
		Forecast	Causality	Forecast	Causality	Forecast	Causality
Detrended GDP	4	0.030	0.008	0.750	0.742	0.069	0.037
	5	0.027	0.001	0.810	0.891	0.007	0.028
	6	0.004	0.000	0.807	0.715	0.005	0.032
Fed Funds Rate	4	1.000	0.005	0.491	0.356	0.085	0.043
	5	0.667	0.020	0.639	0.582	0.038	0.014
	6	0.404	0.023	0.730	0.510	0.046	0.004
Term Spread	4	0.076	0.000	0.373	0.199	0.103	0.007
	5	0.106	0.000	0.386	0.165	0.021	0.003
	6	0.080	0.001	0.513	0.202	0.029	0.003

Notes: The columns labelled "Forecast" display the marginal significance of exclusion F-statistics for the following regressions that forecast the model-based shock $\eta_{i,t}$ using lags of an explanatory variable X_t

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

Here, $i = \{MP, MRS, TECH\}$; $N = \{4, 5, 6\}$; 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 test the hypothesis $\beta_i = 0, \forall i = 1, ..., N$. The columns labelled "Causality" display the marginal significance of exclusion F-statistics for the following Granger-Causality regressions

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

where, again, the F-statistic test the hypothesis $\beta_i = 0, \forall i = 1, ..., N$.

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 (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 the3×1 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 twenty-four endogenous 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)

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)

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)

Consumption Expenditures on NonDurables & Services

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.028 (0.102,0.000)	0.173 (0.375,0.034)	0.118 (0.402,0.015)
Shock to MRS	0.157 (0.263,0.057)	0.106 (0.307,0.012)	0.073 (0.343,0.008)
Shock to Tech	0.073 (0.173,0.011)	0.236 (0.446,0.060)	0.311 (0.570,0.085)
Total of 3 Shocks	0.273 (0.350,0.197)	0.557 (0.676,0.406)	0.589 (0.792,0.353)

Consumption Expenditures on Durables

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.014 (0.094,0.000)	0.059 (0.226,0.013)	0.071 (0.269,0.014)
Shock to MRS	0.217 (0.373,0.075)	0.127 (0.324,0.034)	0.068 (0.218,0.018)
Shock to Tech	0.129 (0.283,0.031)	0.357 (0.539,0.156)	0.375 (0.554,0.156)
Total of 3 Shocks	0.388 (0.498,0.256)	0.578 (0.700,0.430)	0.558 (0.735,0.366)

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)

Housing Starts

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.034 (0.108,0.001)	0.194 (0.290,0.114)	0.201 (0.305,0.117)
Shock to MRS	0.177 (0.277,0.071)	0.191 (0.285,0.103)	0.189 (0.283,0.105)
Shock to Tech	0.031 (0.119,0.000)	0.069 (0.142,0.014)	0.100 (0.196,0.039)
Total of 3 Shocks	0.256 (0.343,0.156)	0.463 (0.563,0.353)	0.501 (0.608,0.402)

Inventory Investment

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.074 (0.184,0.010)	0.096 (0.232,0.037)	0.118 (0.226,0.057)
Shock to MRS	0.017 (0.071,0.000)	0.265 (0.390,0.150)	0.256 (0.374,0.148)
Shock to Tech	0.057 (0.145,0.009)	0.079 (0.204,0.025)	0.168 (0.330,0.074)
Total of 3 Shocks	0.169 (0.261,0.080)	0.475 (0.561,0.382)	0.566 (0.670,0.467)

Net Exports

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.004 (0.023,0.000)	0.010 (0.052,0.001)	0.132 (0.287,0.015)
Shock to MRS	0.020 (0.047,0.004)	0.079 (0.149,0.026)	0.079 (0.229,0.011)
Shock to Tech	0.010 (0.033,0.000)	0.012 (0.041,0.004)	0.023 (0.094,0.005)
Total of 3 Shocks	0.041 (0.070,0.016)	0.107 (0.191,0.054)	0.255 (0.425,0.121)

3 Month 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)

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)

Fama-French Factor Small Stock Factor

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.038 (0.076,0.012)	0.040 (0.066,0.020)	0.045 (0.078,0.026)
Shock to MRS	0.035 (0.075,0.009)	0.072 (0.122,0.034)	0.090 (0.147,0.047)
Shock to Tech	0.012 (0.043,0.000)	0.043 (0.080,0.015)	0.068 (0.120,0.033)
Total of 3 Shocks	0.092 (0.132,0.056)	0.160 (0.206,0.119)	0.210 (0.270,0.161)

Fama-French Factor Book-to-Market Factor

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.030 (0.068,0.006)	0.045 (0.088,0.017)	0.053 (0.099,0.025)
Shock to MRS	0.040 (0.079,0.009)	0.068 (0.120,0.027)	0.078 (0.126,0.038)
Shock to Tech	0.008 (0.036,0.000)	0.027 (0.059,0.009)	0.041 (0.079,0.021)
Total of 3 Shocks	0.086 (0.128,0.047)	0.145 (0.205,0.098)	0.179 (0.244,0.125)

Pound/$ Exchange Rate

Steps ahead:	3-month	12-months	60-months
Shock to MP	0.041 (0.111,0.003)	0.057 (0.147,0.007)	0.211 (0.384,0.072)
Shock to MRS	0.010 (0.059,0.000)	0.013 (0.065,0.002)	0.040 (0.148,0.010)
Shock to Tech	0.022 (0.079,0.001)	0.067 (0.160,0.012)	0.122 (0.245,0.054)
Total of 3 Shocks	0.088 (0.171,0.029)	0.157 (0.256,0.075)	0.405 (0.583,0.242)

Figure 1: Responses to Technology Shock

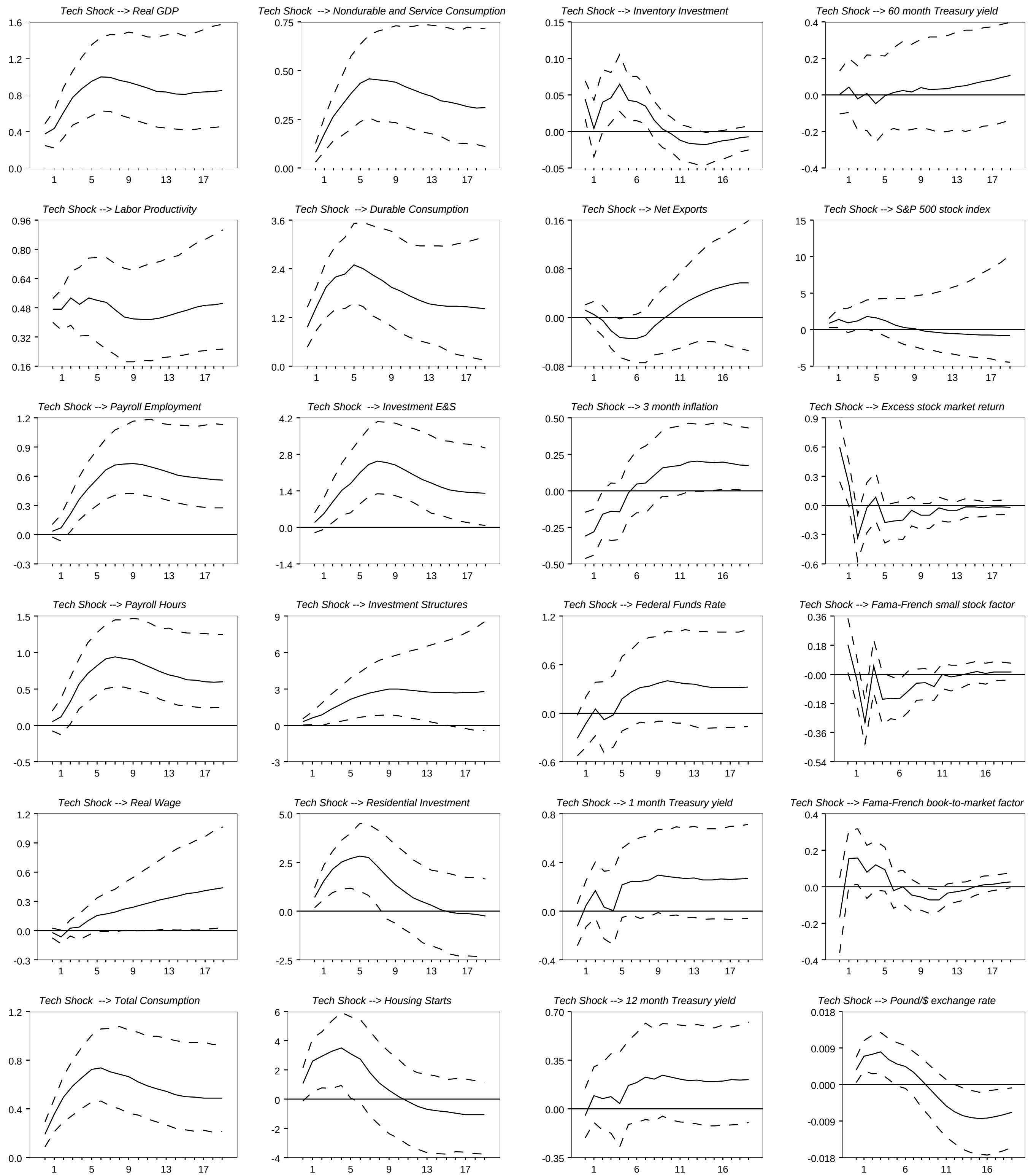


Figure 2: Responses to MRS Shock

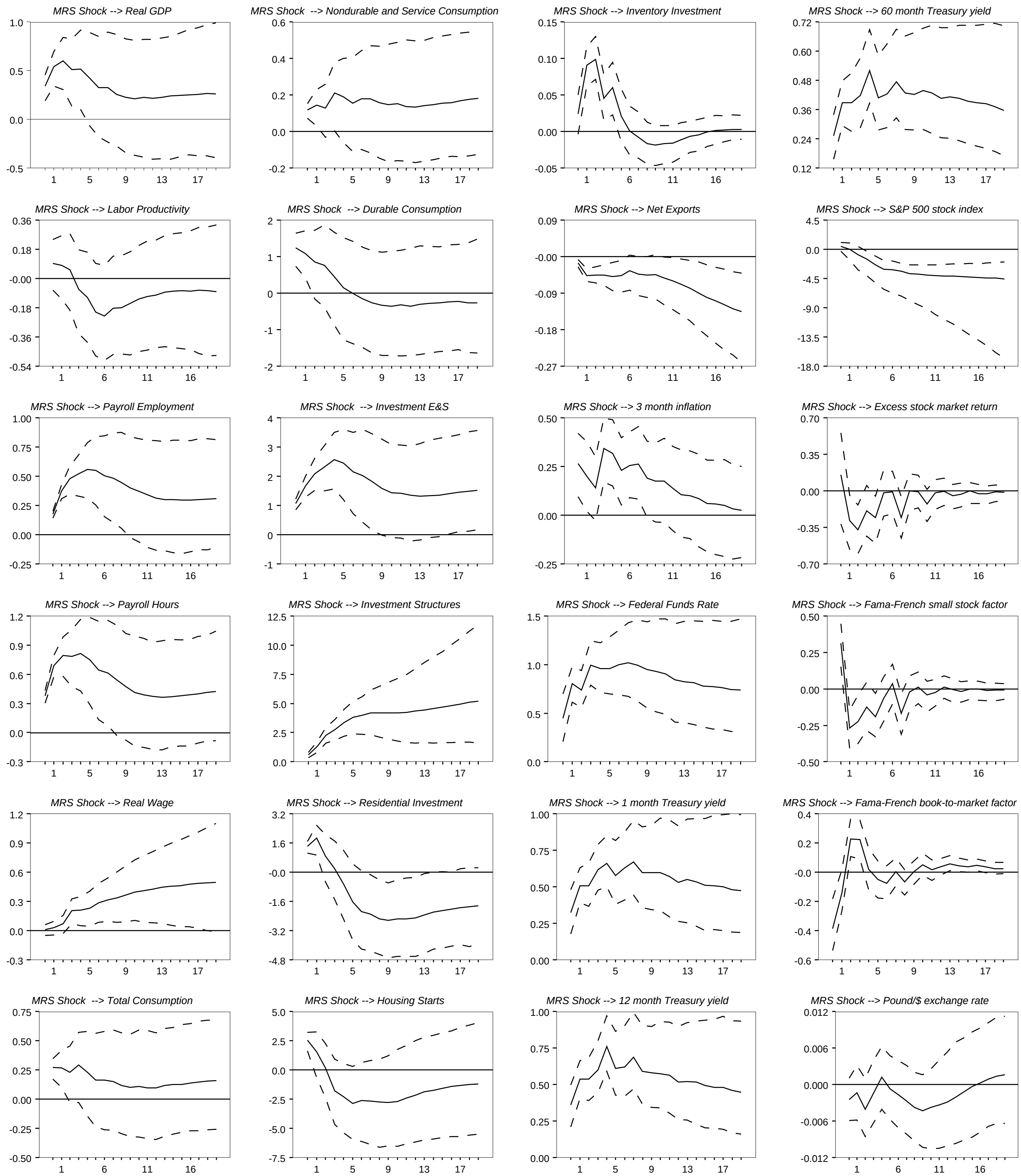


Figure 3: Responses to Monetary Policy Shock

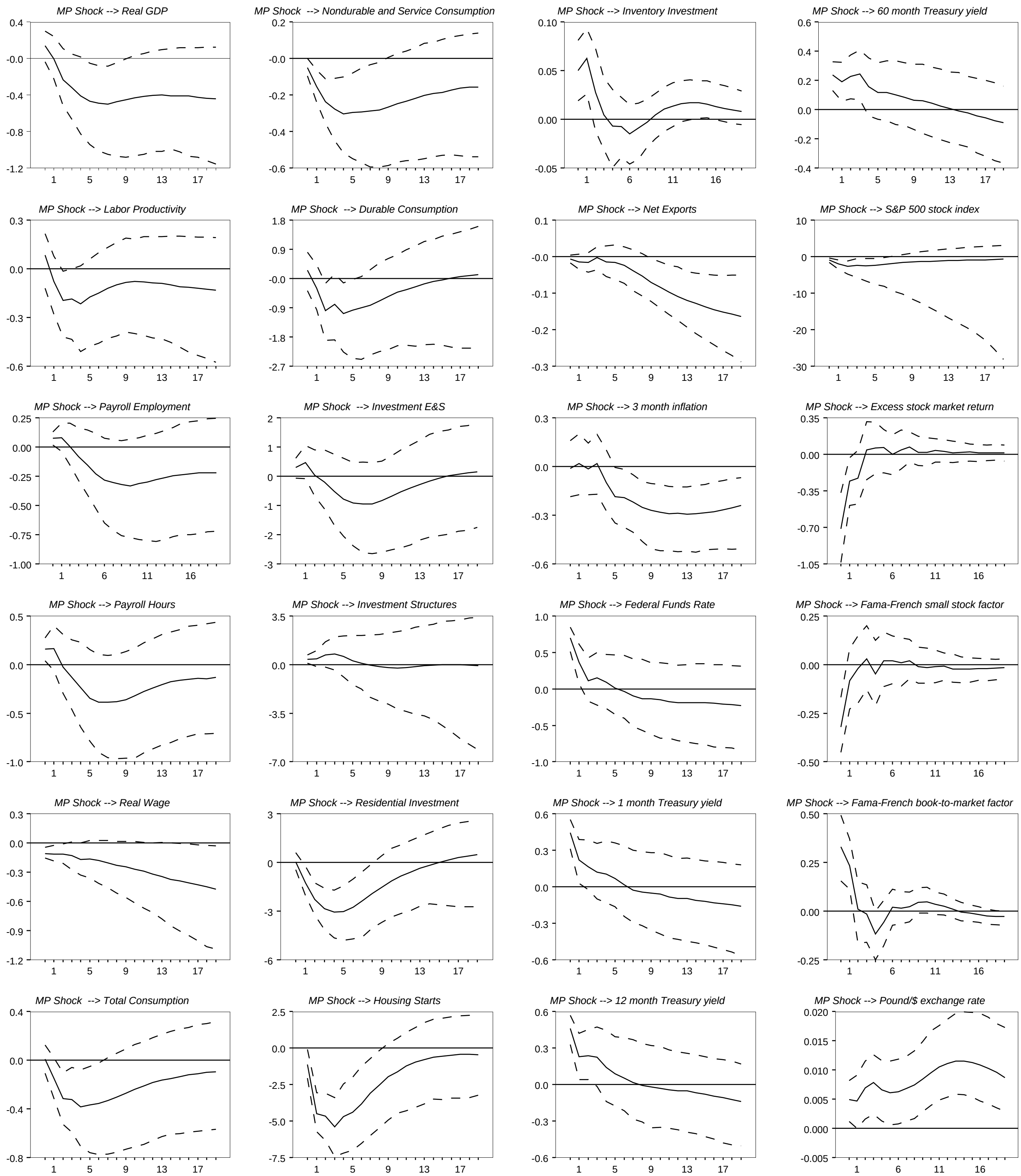
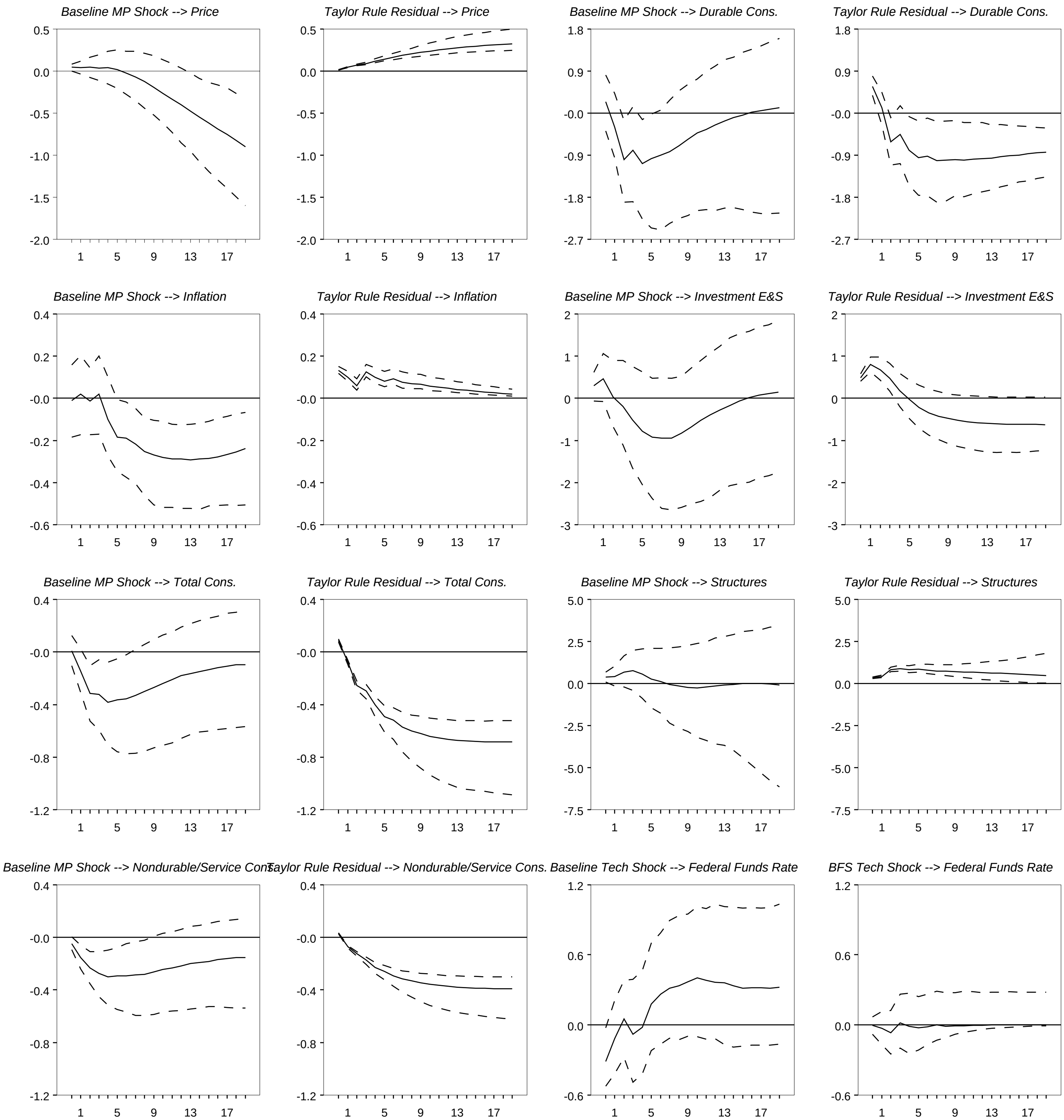


Figure 4

Baseline Shocks vs. Single-Eta Shocks



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