Economic Determinants of the Nominal Treasury Yield Curve

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Abstract

Macroeconomic shocks account for most of the variability of nominal Treasury yields, inducing large shifts in the yield curve level. We develop a new approach to identifying macroeconomic shocks that exploits model-based empirical shock measures. Shocks to preferences for current consumption a¤ect yields through their impact on real rates, expected in‡ation, and term premiums. Technology shocks shift yields primarily through their e¤ect on expected in‡ation. For both shocks, the systematic reaction of monetary policy is an important transmission pathway. These results are similar to those implied by Galí's (1992) structural VAR. The evidence on …scal policy shocks is inconclusive, depending critically on the identi…cation strategy employed.

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1. Introduction

Bond markets rapidly assimilate vast amounts of information about economic activity. Consequently, macroeconomic shocks should influence Treasury yields. The yield curve is often cited as providing information on the current stance of monetary and fiscal policy, as well as expectations of future economic activity, real interest rates, and inflation. (For example, see Bernanke and Blinder (1992), Estrella and Hardouvelis (1991), Blanchard (1985), Mishkin (1990).) More specifically, nominal interest rate movements involve real interest rate movements and changes in expected inflation. Changes in real interest rates are associated with anything that alters the marginal product of capital, the intertemporal marginal rate of substitution for households, or investors' risk tolerance. Inflation expectations are related to expected monetary policy, which in turn is influenced by macroeconomic factors through the central bank's policy rule (such as a Taylor (1993) rule). For these reasons one would expect to find links between movements in the nominal Treasury yields and observed macroeconomic shocks.

While a major theme of finance research is to understand the factors that move the term structure, little work to date has focused on observable macroeconomic factors. Rather, most recent work on the term structure assumes that interest rate changes are driven by unobserved factors. Notable examples include Litterman and Scheinkman (1991), Knez, Litterman and Scheinkman (1994), Backus, Foresi, and Telmer (1998), and the empirical affine term structure literature.[1] An important exception is Ang and Piazzesi (2001). They introduce two observable macroeconomic factors into a Dai and Singleton (2000)-type affine model of the yield curve. The first factor is the first principal component extracted from several measures of real economic activity; the second factor is similarly extracted from several price level indices. They find that macro factors explain up to 85% of the long-horizon variance of shorter-term yields, but have a much smaller effect on long yields. As a result, these factors shift the slope, rather than the level, of the yield curve.

In this paper, we ask how different macroeconomic impulses affect the nominal yield curve. We use a variety of empirical approaches related to the work of Sims (1980, 1986), Bernanke (1986), and Blanchard and Watson (1986), among others. Our initial results are from an atheoretic empirical exercise that simply asks whether the level, slope, and curvature of the yield curve are significantly affected by the block of macroeconomic variables. While we confirm Ang and Piazzesi's (2001) result that most of the variability of short- and medium-term yields is driven by macroeconomic factors, our results for the long-term yield are rather different. We find that macro impulses account for almost 90% of the 5-year yield variance.

[1] See Duffie and Kan (1996), Dai and Singleton (2000) and Backus, Foresi, Mozumdar, and Wu (2001).

We also find that observable macro factors have a substantial, persistent, and statistically significant effect on the level of the term structure, whereas Ang and Piazzesi (2001) attribute virtually all movements in the yield curve level to unobserved latent factors.

Our second set of results provides evidence how specific types of shocks affect the yield curve. To identify economic shocks, we develop an approach that is new to the VAR literature. Instead of imposing *a priori* covariance restrictions on the relation between the VAR innovations and shocks, we infer these relationships from empirical measures of economic shocks that economists have proposed, often based on dynamic general equilibrium models. Our model-based measures include: Basu, Fernald, and Shapiro's (2001a,b) measure of technology shocks; Blanchard and Perotti's (2002) measure of fiscal policy shocks; and a measure of marginal-rate-of-substitution (MRS) shocks similar to that studied by Hall (1997). We show how this information is easily incorporated into the analysis of VAR impulse response functions. We contrast this approach with a more conventional structural VAR due to Galí (1992). Galí's approach identifies fundamental macroeconomic impulses as an aggregate supply shock, an IS shock, and a monetary policy shock.

We find that both our MRS shock and the Galí (1992) IS shock move output and inflation in the same direction. Many empirical macroeconomists refer to this sort of impulse as an aggregate demand shock (e.g., see Blanchard (1989)). An expansionary shock of this type increases both expected inflation and real interest rates, inducing a large, significant, and persistent response in all nominal rates. In contrast, the technology shock and the Galí (1992) aggregate supply shock move output and inflation in opposite directions. An expansionary shock of these types drives real interest rates up and expected inflation down, so its effect on nominal interest rates is, in principle, ambiguous. However, for most of our identification strategies the expected inflation response dominates, so the expansionary shock tends to reduce interest rates of all maturities. Our model-based measure of fiscal shocks does not have a significant impact on interest rates. However, an alternative identification approach for fiscal shocks, due to Ramey and Shapiro (1998), implies a significant yield curve response to fiscal impulses. Thus, the evidence on the interest rate response to fiscal shocks remains ambiguous, depending critically on the identification procedure that is used.

Our third set of results relates to the transmission mechanisms by which these shocks move the yield curve. We find that the systematic response of monetary policy is an important pathway whereby macroeconomic shocks affect interest rates. Monetary policy generally reacts to these shocks in the manner predicted by the Taylor (1993) principle: shocks that increase expected inflation or the gap between actual and potential output tend to increase the Federal funds rate. Longer-term interest rates are affected by expectations of changes in the funds rate. A second transmission mechanism is that macroeconomic shocks can directly affect longer-term interest rates by moving term premiums.

Our approach differs from that of Ang and Piazzesi (2001) in three important ways. First, we allow monetary policy to feed back on macroeconomic variables, as in Bernanke and Blinder (1992), Sims (1992), and Christiano, Eichenbaum, and Evans (1999). Second, rather than simply looking at two atheoretical macroeconomic factors, we attempt to identify the fundamental economic shocks and to look at the way these shocks affect interest rates. Third, we do not impose no-arbitrage. Ang and Piazzesi (2001) provide evidence that the out-of-sample forecasting ability of VARs with term structure variables is enhanced when the no-arbitrage condition is imposed. However, imposition of no-arbitrage makes it more difficult to compute standard errors for impulse responses and variance decompositions, which Ang and Piazzesi (2001) do not report.

The remainder of this paper is structured as follows. In section 2, we describe our basic statistical framework. In section 3, we conduct a preliminary empirical exploration on the effect of macroeconomic factors on the yield curve. This section revisits some of the questions raised in Ang and Piazzesi (2001). Section 4 develops our identification methodology that uses model-based shock measures, and section 5 explains how we implement this methodology empirically. Section 6 discusses two alternative identification strategies: the Galí (1992) approach, and an alternative way of using our model-based measures. Section 7 presents our empirical findings. Section 8 concludes the paper.

2. Basic statistical framework

Our goal is to quantify the importance of macro shocks for movements in Treasury yields. To that end, we use the following vector autoregression (VAR) framework throughout our empirical analysis. Let Z_t be an $n \times 1$ vector of macroeconomic variables at time t, and let R_t denote an $m \times 1$ vector of zero-coupon Treasury yields of different maturities. We include the Federal Funds rate in Z_t as the instrument of monetary policy. We estimate various restricted versions of the following structural VAR:

$$\begin{bmatrix} A & \mathbf{0} \\ G & H \end{bmatrix} \begin{bmatrix} Z_t \\ R_t \end{bmatrix} = \begin{bmatrix} \tilde{A}(L) & \mathbf{0} \\ \tilde{C}(L) & \tilde{D}(L) \end{bmatrix} \begin{bmatrix} Z_{t-1} \\ R_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \gamma_t \end{bmatrix} \tag{1}$$

where A and H are nonsingular square matrices; G is a rectangular matrix; $\mathbf{0}$ is the zero matrix with appropriate dimensions; and $\tilde{A}(L), \tilde{C}(L)$, and $\tilde{D}(L)$ are matrix polynomials in the lag operator L. The process $\left[\varepsilon_t', \gamma_t'\right]'$ is an i.i.d. vector of mutually and serially uncorrelated shocks whose variance is the identity matrix. For most of our exercises we impose restrictions on system (1) that identify the elements of ε_t as structural macroeconomic shocks. The elements of γ_t are yield shocks that are analogous to Ang and Piazzesi's (2001) vector of latent financial variables. The zero restrictions on the upper right-hand blocks of the coefficient matrices in (1) imply that neither current nor lagged yields R_{t-i}, $i \geq 0$ nor the yield shocks γ_t enter the law of motion for the macroeconomic variables Z_t. In other words, we assume that current and lagged Z_t are a sufficient state vector for spanning the space of all macroeconomic driving shocks. We impose these restrictions to ensure comparability with Ang and Piazzesi (2001) and, in section 6.1, with Galí (1992).[2]

We estimate system (1) via ordinary least squares using the following reduced form:

$$\begin{bmatrix} Z_t \\ R_t \end{bmatrix} = \begin{bmatrix} a(L) & \mathbf{0} \\ c(L) & d(L) \end{bmatrix} \begin{bmatrix} Z_{t-1} \\ R_{t-1} \end{bmatrix} + \begin{bmatrix} u_t \\ v_t \end{bmatrix} \tag{2}$$

where $\left[u_t^{\prime}\ v_t^{\prime}\right]^{\prime}$ is the vector of OLS residuals. If the matrix A is known, then the structural macroeconomic shocks ε_t can be recovered from the OLS residuals via the relation

$$Au_t = \varepsilon_t \tag{3}$$

To identify the n^2 elements of matrix A requires n^2 restrictions. Since the variance-covariance matrix of ε_t is normalized to be the identity matrix, $n\,(n+1)\,/2$ restrictions are provided by

$$E\left[u_t u_t^{\prime}\right] \equiv \Sigma_u = \left(A^{-1}\right)\left(A^{-1}\right)^{\prime}. \tag{4}$$

Therefore, an additional $n\,(n-1)\,/2$ *a priori* restrictions are needed to identify ε_t. Once ε_t is identified, variance decompositions and impulse responses can be computed.

3. Initial empirical exploration

Our first exercise is simply an exploration of the data's properties. The data vector is given by $Z \equiv (Y, PCOM, P, FF)^{\prime}$, where Y denotes the logarithm of industrial production, $PCOM$ denotes the smoothed change in an updated version of the index of sensitive materials prices originally published in the index of leading indicators, P denotes the logarithm of the personal consumption expenditure chain-weight price index, and FF denotes the Federal funds rate. The yields we use here, and throughout the paper, are the 1-month, 12-month, and 60-month zero coupon bond yields from the CRSP data base. The data are monthly, from January 1959 through December 2000. The VAR incorporates 12 lags.

It is convenient expositionally to posit a lower-triangular structure for matrices A and H in system (1). This is equivalent to a simple recursive orthogonalization of the VAR residuals $\{u_t, v_t\}$. The order of orthogonalization for u_t is: $\{Y, PCOM, P, FF\}$. We give

[2] As a robustness check we also re-estimate the models allowing lagged yields to enter the law of motion for Z_t. For all models, the resulting point estimates for impulse responses are similar to those obtained when we impose the zero restrictions in equation (2), and inference is unaffected.

no structural interpretation to the elements of ε_t thus constructed, except to interpret them as linear combinations of the underlying (unobserved) macroeconomic factors.

Our interest here is to revisit the key questions explored by Ang and Piazzesi (2001): What fraction of yield variance can be accounted for by macro variables, and can macro variables induce significant shifts in the level of the yield curve? Results for the first question are in Table 1, which displays the fraction of the conditional variance of each yield (at three time horizons) attributable to each of the orthogonalized residuals. While only 32% of the one-month-ahead conditional variance of the shortest yield is accounted for by macro variables (and most of this is due to Federal funds rate orthogonalized innovations), fully 91% of the 60-month ahead variance of this yield is attributable to macro factors. Similarly, the fraction of the one-month ahead conditional variance for the 12- and 60-month yields explained by macro factors are only 35% and 20%, respectively. When we look at the 60-month ahead variance, these percentages rise dramatically to 92% and 89% for these two bonds. For all yields, most of the variance at the 60-month horizon is explained by the orthogonalized innovations associated with industrial production and sensitive materials prices.

Our estimates of the fraction of 60-month ahead variance explained by macro factors for the one- and 12-month yields are similar to those reported by Ang and Piazzesi (2001). However, our estimate of this statistic for the 60-month yield is much higher than that reported by Ang and Piazzesi (2001). They report that only 48% of the 60-month ahead variance of the long bond is explained by macroeconomic factors.

We now ask whether macro shocks shift the level of the yield curve as well as the slope and curvature. To do so, we must give precise definitions for level, slope and curvature. Following Cochrane (2001), we construct the three principal components of the 1-month, 12-month, and 60-month yields at each date. We associate the level of the yield curve with the first principal component, the slope with the second principal component, and the curvature with the third component.[3] For example, the first principal component is a linear combination of the three yields, where the weights α_i are the elements of the eigenvector associated with the largest eigenvalue

$$y_t^{level} = \alpha_1 \; y_t^1 + \alpha_{12} \; y_t^{12} + \alpha_{60} \; y_t^{60} \tag{5}$$

where y_t^j denotes the j-month yield. The weights for this principal component decomposition are displayed in Table 2. Notice that the level weights are approximately equal, the slope weights on the 1-month and 60-month yields are approximately the same magnitude but

[3] Ang and Piazzesi (2001) associate the level of the yield curve with an equally weighted average of the 1-month, 12-month, and 60-month yields. Their measure of the slope is the difference between the 60-month yield and the 1-month yield, and their measure of curvature is the sum of the 1-month and 60-month yields minus twice the 12-month yield. Although we use a slightly different characterization, the differences between our measures and Ang and Piazzesi's are small.

opposite signs, with the slope weight on the 12-month yield close to zero, and the curvature weight on the 12-month yield is larger and opposite in sign from the curvature weights on the other two yields. These measures of level, slope, and curvature represent an orthogonal decomposition of the vector time series of yields.

In Figure 1, we plot the responses, in percentage points per annum, of the three yields (rows 1 - 3 in the figure), as well as the responses of level, slope, and curvature (rows 4 - 6), to the positive orthogonalized innovations in our four macro variables. The dashed lines give Bayesian 90% probability error bands for the impulse responses, computed using 500 Monte Carlo draws from the posterior distribution of the model's parameters.[4] Note that the orthogonalized residuals to industrial production and to the commodity price index (columns 1 and 2 of the figure) shift all three yields upwards. These responses are large: the maximal responses of the 1-, 12-, and 60-month yields to a one-standard deviation shock to the Y orthogonalized residual are 24, 23, and 16 basis points, respectively; the corresponding maximal responses of these yields to the $PCOM$ residual are 33, 32, and 24 basis points, respectively. Because the yields respond roughly in parallel, the yield level shifts upwards. This level response is large and very persistent; the error bands put a high probability on a positive level response. In contrast, the yield slope and yield curvature responses are small, and the error bands generally straddle the zero response.

Our finding of substantial level responses to macro shocks contrasts with Ang and Piazzesi's (2001) results. They found that macro factors induced a substantial response in the yield curve slope, but they concluded that level shifts were primarily driven by latent factors. In our system, macroeconomic factors have a much larger impact on the long yield. A key difference between the two approaches is that Ang and Piazzesi (2001) do not allow systematic monetary policy to influence macroeconomic variables. In particular, their macro block is exogenous with respect to all interest rates, including the Federal funds rate, which is the monetary policy instrument. Our system (1) allows for richer dynamic interactions between this monetary policy instrument and the other macroeconomic variables. As we shall see in section 7, below, monetary policy is a key pathway whereby macro shocks affect the Treasury yield curve.

[4] We display percentile bands around the estimated impulse response functions. Our uninformative prior distributions on Σ_u and the VAR coefficients in $A(L)$, $C(L)$, and $D(L)$ are the standard ones described in the RATS manual (Doan, 2000) and Sims and Zha (1999). We follow Zha's (1999) development of the posterior distributions in block recursive VAR systems.

4. Identifying structural shocks using model-based measures

According to the evidence of section 3, a large fraction of the interest rate variance for all maturities is accounted for by macroeconomic impulses. Furthermore, there are combinations of macroeconomic innovations that have large, significant, and long-lived effects on the level of the yield curve. However, unless substantially more structure is imposed on the VAR in equation (1) this description of the data's conditional second moment properties represents an incomplete characterization of the economic determinants of the nominal yield curve. According to equation (3), identification of the structural shock vector ε_t requires restricting matrix A. We propose in this section an approach that closely ties the identifying restrictions to specific economic theories. In particular, as in Prescott (1986) and Hall (1997), we exploit the ability of economic models to guide directly the construction of empirical measures of fundamental economic impulses, such as technology shocks, fiscal policy shocks, and shocks to households' marginal rate of substitution (MRS) between consumption and leisure. As a result, few prior restrictions are placed on the covariance structure of the VAR innovations u_t. As much as possible, we allow the model-based measures to dictate the VAR identification of macroeconomic shocks ε_t.

Let η_t denote the vector of observable model-based measures. (In section 5 we describe in detail how we construct these measures from data.) We assume that these measures represent noisy measures of the true underlying shocks ε_t. Specifically,

$$\eta_t = D\ \varepsilon_t + w_t \tag{6}$$

where D is a non-singular $(n \times n)$ matrix and w_t is a vector of measurement errors independent of ε_t (and therefore of u_t). To identify the model, we must uniquely determine the matrices A and D. To that end, substitute equation (3) into equation (6) to get

$$\eta_t = Cu_t + w_t \tag{7}$$

where

$$C \equiv DA \tag{8}$$

or, equivalently,

$$A = D^{-1}C \tag{9}$$

This condition is important. Since w_t is uncorrelated with u_t, the matrix C can readily be estimated from equation (7) by ordinary least squares. Therefore, A could be identified with no *a priori* restrictions if the n^2 elements of D were known. In effect, this shifts identifying restrictions from the matrix A to matrix D.

Using equations (4) and (9), one obtains

$$DD' = C\Sigma_u C'. \tag{10}$$

The C and Σ_u matrices on the right-hand side of equation (10) can be estimated directly, so equation (10) imposes $n(n+1)/2$ restrictions on D. Identification of D then requires an additional $n(n-1)/2$ *a priori* restrictions. Arguably, restrictions on D are easier to justify than restrictions on A, since the former maps underlying structural shocks into their empirical counterparts, while the latter maps the underlying shocks to the VAR residuals. For example, D may be diagonal, in which case the η measures are contaminated only by classical measurement error. Alternatively, theory and measurement limitations may indicate that some η measures are linear combinations of the underlying shocks. In that case, D would have some non-zero off-diagonal elements. We discuss the specific identifying assumptions we impose on D in section 5, below.

When the system is exactly identified, D can be computed directly from equation (10) as the unique factorization of $C\Sigma_u C'$ satisfying the identifying restrictions. When the system is overidentified, neither equation (4) nor equation (10) will hold exactly in finite samples. Nevertheless, one can still estimate D by using the maximum likelihood procedure described in Hamilton (1994, pp.331-332). Once D is determined, matrix A can be computed using equation (9).

5. Model-based measures of structural shocks

Implementing the model-based identification strategy, described above in section 4, requires measuring macroeconomic driving shocks. In this section we describe four measured shocks: technology, preference, fiscal policy and monetary policy.

5.1. 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.[5] Basu, Fernald, and Shapiro (2001b) provide a recent estimate of technology innovations that attempts to reduce these influences. Ignoring industry composition effects, their aggregate analysis specifies production as follows:

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

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

$$\ln z_t = \mu + \ln z_{t-1} + \varepsilon_{Tech,t} \tag{11}$$

where Y, z, v, K, e, and N are the levels of output, technology, capital utilization rate, capital stock, labor effort, and labor hours.[6] 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}.[7] 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.

5.2. 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.[8] Consider a representative consumer with the following utility specification that includes external habit persistence

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

$$\ln \xi_t = \rho(L) \ln \xi_{t-1} + \varepsilon_{MRS,t} \tag{12}$$

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

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

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

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

lead to the following intratemporal Euler equation (or MRS relationship)

$$\frac{\xi_t \left(C_t - b\overline{C}_{t-1}\right)^{-\gamma}}{N_t^{\phi}} = 1/W_t \tag{13}$$

where W is the real wage. Taking logs, one obtains

$$ln\ \xi_t = \phi\ ln\ N_t - lnW_t + \gamma ln\left[C_t - b\overline{C}_{t-1}\right]. \tag{14}$$

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

We use equation (14) to obtain an empirical measure of $\ln \xi_t$. We then compute our model-based empirical measure $\eta_{MRS,t}$ of the MRS shock $\varepsilon_{MRS,t}$ as the residual from the OLS estimate of equation (12). Our data are quarterly and extend from 1964:I to 2000:IV. Consumption is measured by per capita nondurables and services expenditures in chain-weighted 1996 dollars. Labor hours correspond to hours worked in the business sector per capita. The real wage corresponds to nominal compensation per labor hour worked in the business sector deflated by the personal consumption expenditure chain price index. The hours and compensation data are reported in the BLS productivity release. 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 (12). 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 $\rho(L)$. [9]

Many macroeconomic researchers have recently offered several differing interpretations for the random marginal rate of substitution shifter ξ_t in equation (13).[10] First, the home

[9] 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.

[10] 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.

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 (13). In particular, in the Calvo pricing environments considered by Christiano, Eichenbaum, and Evans (2001) and Galí, Gertler, Lopes-Salido (2001), alternative versions of (13) hold. Third, Chari, Kehoe, and McGrattan (2002) 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.

5.3. Fiscal Policy Shocks

The modern business cycle literature that includes fiscal policy effects has focused primarily on exogenous specifications of government spending and tax rates.[11] To relate these theoretical studies to aggregate data requires distinguishing between the exogenous and endogenous components of fiscal policy. The recent empirical literature on fiscal policy shocks includes two distinct approaches to this problem. Blanchard and Perotti (2002) construct a quarterly series of exogenous fiscal shocks by using regression methods to control for the systematic response of fiscal policy. In contrast, Ramey and Shapiro (1998) use a narrative approach to identify dates when large, exogenous fiscal policy shocks occurred. Our initial exercise uses the Blanchard and Perotti (2002) methodology,[12] which we summarize in this section. Later, we conduct an exercise in the spirit of Ramey and Shapiro (1998). We defer discussion of that approach to section 7.3, below.

Blanchard and Perotti (2002) start with measures of GDP, government spending excluding transfers, and tax receipts net of transfers. The latter two variables include federal, state, and local measurements. Blanchard and Perotti control for the automatic responses of spending and taxes to changes in GDP, using measures of the elasticity of different types of taxes, transfers, and spending to output. Additional restrictions are imposed to identify exogenous shocks to taxes and government spending.[13] We construct our model-based

[11] Baxter and King (1993) and Christiano and Eichenbaum (1992) study permanent and transitory changes in exogenous government purchases. Braun (1994) and McGrattan (1994) study transitory changes in exogenous tax rates. An alternative approach is taken by Leeper and Sims (1994): they allow tax rates to respond systematically to the state of the economy.

[12] We thank Roberto Perotti for providing us with his time series of fiscal policy shocks.

[13] Blanchard and Perotti (2001) estimate their VAR under two different trend assumptions. First, they incorporate deterministic time trends; second, they allow for stochastic trends. We have done our analysis with fiscal shocks computed both ways. The results are very similar, so we only display the results for the

empirical measure η_{Fiscal} as a shock to the government deficit, defined as the difference between Blanchard-Perotti's government spending and tax shocks.[14] We treat η_{Fiscal} as a noisy measure of the underlying fiscal policy shock ε_{Fiscal}.

5.4. Accounting for Monetary Policy Shocks

The effects of monetary policy shocks on the term structure have been studied elsewhere,[15] and are not the focus of this paper. However, to isolate the effects of technology, MRS, and fiscal shocks, we control for monetary policy impulses to ensure that the effects of monetary policy shocks are not incorrectly ascribed to these other shocks. To do so, we introduce an empirical measure of monetary policy shocks, denoted η_{MP}. We use an updated version of the monetary policy shock measure in Christiano, Eichenbaum, and Evans (1996). This measure is derived from an identified VAR using the following variables: the logarithm of real GDP; the logarithm of the GDP chain-weighted price index; the smoothed change in the index of sensitive materials prices used in section 3; the Federal funds rate; the logarithm of nonborrowed reserves; and the logarithm of total reserves. The data run from 1959:I through 2000:IV.

5.5. Behavior of the Model-Based Shocks

In this section we explore the statistical properties of the model-based shock measures. Table 3 displays the contemporaneous correlation matrix for η_t. Note that the correlations are fairly low, with the exception of $corr\left(\eta_{Tech}, \eta_{Fiscal}\right)$, which exceeds 0.30. These non-zero correlations contradict the usual assumption in the structural VAR literature that the fundamental shocks be mutually uncorrelated. In section 5.6, below, we describe an identification approach that explicitly takes these correlations into consideration.

According to equation (7), the model-based measures only provide useful information for identifying A if they are correlated with the VAR residuals u_t. Table 4 provides evidence on these correlations for the data we use. It displays the R^2s for the OLS regressions in system (7) using the measures of $\eta_t = (\eta_{MP}, \eta_{MRS}, \eta_{Tech}, \eta_{Fiscal})'$ described in sections 5.1 - 5.4. The variables in our macro VAR block are quarterly analogues to the monthly measures used in section 3: real GDP, the GDP price deflator, the commodity price index $PCOM$, and the Federal funds rate. The only problematic shock measure in Table 4 is the fiscal shock, whose R^2 is only 8.7%.[16] This suggests that our fiscal shock measure η_{Fiscal} may not provide

model with deterministic time trends.

[14] We have also performed the analysis with the individual tax and spending shocks. The results are qualitatively unchanged, although the impulse responses to these individual shocks are smaller.

[15] See Gordon and Leeper (1994), Bernanke, Gertler, and Watson (1997), and Evans and Marshall (1998).

[16] Our measure of η_{Fiscal} is the difference between the government spending shock and the tax shock, both

strong identification for an underlying fiscal shock in the context of our VAR system. As a result, caution should be exercised in interpreting the responses to the fiscal shock implied by this exercise.

Figure 2 displays centered 3-quarter moving averages of the model-based empirical measures η_t for 1964 through 1999. Moving averages are displayed to reduce the quarter-to-quarter volatility. For comparability, the η_t measures in Figure 2 have been transformed to have a unit variance. Positive values of η_{MRS} and η_{Tech} are expansionary; positive values of η_{Fiscal} imply an increase in the fiscal deficit; and positive values of η_{MP} imply an increase in the Federal funds rate.

The MRS shock appears to be an important ingredient in U.S. business cycles over our sample period. First, η_{MRS} is negative during all five recessions in our sample. The MRS shock takes on its largest negative values during the two deepest recessions, 1973-75 and 1981-82. The large negative MRS shock in 1980 may have been associated with the Carter credit control program. Second, on other occasions when $\eta_{MRS} < 0$ by a substantial amount, other shocks had offsetting effects. For example, $\eta_{MRS} < 0$ in 1976, 1986, and 1991-92. Each of these instances appears to have been offset by relatively positive technology shocks. Third, positive MRS shocks tend to be associated with periods of economic expansion. The ends of the three largest recessions were accompanied by large, positive MRS shocks.

Technology shocks also contribute to economic fluctuations, although the relationship may be more complex than for MRS shocks. During each of the five recessions, $\eta_{Tech} < 0$ for some portion of the episode. Unlike the MRS shock, however, technology is positive during the relatively mild 1969-70 recession and just before the end of the 1973-75 recession. During expansions, technology shocks are often positive. The increase in productivity growth in the second half of the 1990s is apparent in these measures, as Basu, Fernald and Shapiro (2001a) discuss.

Monetary and fiscal policy shocks seem to have less importance for economic fluctuations than the MRS and technology shocks. For fiscal deficit shocks, the time series often lines up with a narrative description of policy over this period. The mid-1960s were a period of rising government spending, followed by a temporary tax surcharge at the end of the decade. The negative fiscal shocks in the mid-1970s may be due to declining defense expenditures and creeping tax burdens. An overall pattern of positive deficit shocks emerges throughout most of the 1980s, consistent with the fiscal policy of the Reagan administration. For 1993-97, $\eta_{Fiscal} < 0$ seems consistent with increases in income taxes and reductions in government spending growth due to political gridlock. The monetary policy shocks in Figure 2 indicate

estimated by Blanchard and Perotti (2000). When we estimate regression (7) using the spending shock or the tax shock individually, the R^2s are all below 6%.

that monetary policy was relatively expansionary throughout the 1970s, prior to the Volcker regime. The tight monetary policy from 1979 to 1982 is apparent. From this period until the end of the sample, monetary policy shocks appear to have been substantially less volatile.

5.6. Identifying restrictions

Given the empirical estimates of η_t, the key step in the identification is to specify restrictions on D, the mapping from the model-based measures η to the true underlying shocks ε in equation (6). A straightforward approach would be to assume that each element of η_t equals the corresponding element of ε_t plus measurement error. In this case, D would be diagonal. We find that the data strongly reject this model. Alternatively, some η measures may be linear combinations of the underlying shocks, perhaps due to mismeasurement in the way the series in η were computed. This could account for the correlation structure among η_{it} elements, described in Table 3, and would imply non-zero off-diagonal elements of D.

As we noted in section 5.1, there is a large literature on possible mismeasurement of technology shocks. Evans (1992) points to possible contamination of technology shocks by monetary policy; Burnside, Eichenbaum, and Rebelo (1993) discuss the problem of unobserved labor hoarding, and Burnside and Eichenbaum (1996) note the problem of variable capital utilization. While the Basu-Fernald-Shapiro technology measure that we use in this paper attempts to correct for many of these sources of mismeasurement, it may do so imperfectly. Consequently, we wish to allow for the possibility that η_{Tech} may be a linear combination of several shocks. Our baseline case is the following specification of system (6):

$$\begin{bmatrix} \eta_{MP} \\ \eta_{MRS} \\ \eta_{Tech} \\ \eta_{Fiscal} \end{bmatrix} = \begin{bmatrix} d_{11} & 0 & 0 & 0 \\ 0 & d_{22} & 0 & 0 \\ d_{31} & d_{32} & d_{33} & 0 \\ d_{41} & d_{42} & d_{43} & d_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_{MP}^{Base} \\ \varepsilon_{MRS}^{Base} \\ \varepsilon_{Tech}^{Base} \\ \varepsilon_{Fiscal}^{Base} \end{bmatrix} + w \tag{15}$$

where the notation ε_i^{Base} denotes the baseline identification strategy. Note that specification (15) is overidentified: it imposes seven zero restrictions, whereas exact identification requires only six restrictions. Specification (15) assumes that our monetary policy and MRS measures equal the true underlying shock plus classical measurement error. In contrast, η_{Tech} is allowed to incorporate the influence of the true underlying monetary policy and MRS shocks. Note that we do not permit any of these three measures to be contaminated by the underlying fiscal shocks. The reason for this assumption is that the fiscal policy shock measure has the smallest correlation with the VAR innovations u_t of all of our η_{it} elements. (See Table 4.) Consequently, this row of the matrix C is likely to be estimated imprecisely, so we wish to limit the influence of the fiscal policy measure on the other analyses.[17] Further-

[17]With specification (15), the coefficients in the regression of η_{Fiscal} on u_t only affect the identification of

more, Blanchard and Perotti's (2002) approach uses only three variables: GDP, government spending, and government taxes. It can be argued that this measure has not been projected onto innovations from omitted variables that would be included in larger systems. These considerations motivate us to restrict the potential influence of the fiscal policy measure on the identification of the other shocks.

This baseline identification strategy assumes that η_{MP} and η_{MRS} are clean measures (subject to classical measurement error) while η_{Tech} is contaminated. As a robustness check, we consider what happens when we reverse this assumption by assuming that the technology shock is cleanly measured by η_{Tech}, while allowing η_{MP} and η_{MRS} to be contaminated by the technology shock. We explore this alternative with the following exactly identified specifications:

$$\begin{bmatrix} \eta_{MP} \\ \eta_{MRS} \\ \eta_{Tech} \\ \eta_{Fiscal} \end{bmatrix} = D_i^{Alt} \begin{bmatrix} \varepsilon_{MP}^{Alt} \\ \varepsilon_{MRS}^{Alt} \\ \varepsilon_{Tech}^{Alt} \\ \varepsilon_{Fiscal}^{Alt} \end{bmatrix} + w,$$

where

$$D_1^{Alt} = \begin{bmatrix} d_{11} & 0 & d_{13} & 0 \\ d_{21} & d_{22} & d_{23} & 0 \\ 0 & 0 & d_{33} & 0 \\ d_{41} & d_{42} & d_{43} & d_{44} \end{bmatrix} \tag{16}$$

and

$$D_2^{Alt} = \begin{bmatrix} d_{11} & d_{12} & d_{13} & 0 \\ 0 & d_{22} & d_{23} & 0 \\ 0 & 0 & d_{33} & 0 \\ d_{41} & d_{42} & d_{43} & d_{44} \end{bmatrix} \tag{17}$$

6. Two Alternative Identification Strategies

6.1. Galí's identified VAR

Since the identification approach discussed in section 4, above, is new to the literature, we think it useful to contrast its implications with a more conventional procedure. Galí (1992) is a widely-cited structural VAR paper that rigorously analyzes a large number of driving shocks. Galí's (1992) identification strategy imposes a mixture of long-run restrictions and contemporaneous impact restrictions to identify the following four economic shocks: a long-run aggregate supply shock, $\varepsilon_{Supply}^{Galí}$, a transitory IS shock that affects aggregate demand,

$\varepsilon_{Fiscal}^{Base}$, not the other elements of ε^{Base}.

$\varepsilon_{IS}^{Galí}$, a monetary policy shock, $\varepsilon_{MP}^{Galí}$, and a residual macroeconomic shock.[18] The macro-block vector $Z \equiv (\Delta Y, FF, FF - \Delta P, \Delta M - \Delta P)'$, where: ΔY denotes the log difference in industrial production, FF denotes the Federal funds rate, $FF - \Delta P$ denotes the real interest rate (where ΔP is the log difference in the CPI), and $\Delta M - \Delta P$ denotes the change in real M1 balances. The data are monthly, from January 1959 through December 2000. Identification is achieved with six restrictions on the covariance structure of the innovations. First, the monetary policy, IS, and residual macroeconomic shocks have no long-run effect on output; these restrictions identify the long-run supply shock. Second, the monetary policy and residual macro shocks have no contemporaneous effect on output; knowledge of the long-run supply shock and these two restrictions identify the IS shock. Third, one additional identifying restriction is necessary to identify the remaining two shocks. An additional restriction that Galí considers simply deletes the price data from the monetary authority's contemporaneous information set. This identifies the monetary policy shock directly.[19]

6.2. Using model-based shocks directly

A final approach we use is to separately include each of the model-based empirical measures directly in the VAR. The advantage of this procedure is that it lets each model-based measure speak for itself. The disadvantage is that it blurs the effects of the correlation between η_i and η_j, documented in Table 3. We compute responses to the η measures in the following way. We include a single element of η_t as the first element of Z_t in equation (1), and then use a recursive identification scheme. (That is, we impose that matrices A and D be lower triangular.) The resulting shock will be denoted ε_i^{Single}. For example, to identify the economic shock $\varepsilon_{MRS}^{Single}$, we compute an 8-variable VAR using the following quarterly variables: η_{MRS}, real GDP, the GDP price index, $PCOM$, the Federal funds rate, and the one-, 12-, and 60-month zero coupon bond yields. The VAR has four quarters of lags. To identify each of the four economic shocks ε_i^{Single} in turn, we include the corresponding model-based measure η_i into the vector Z.[20]

[18] Galí considered some identification schemes where this residual shock was interpretable as a money demand shock. In our specification, this interpretation is tenuous. Since the residual shock plays an insignificant role in interest rate determination, we do not discuss it further.

[19] A detailed discussion of the implementation of these restrictions is available from the authors.

[20] Note that ε_i^{Single} is the residual after regressing η_i on its own lags and lags of the macro variables. This purges ε_i^{Single} of any remaining correlation with lagged information. Another approach would be to regress η_i on a constant only, and use the residual as a measure of ε_i^{Single}. When we do so, all results are qualitatively unchanged.

7. Empirical Results

In this section we explore how macroeconomic shocks affect the term structure using the identification strategies described in sections 4, 6.1, and 6.2. The results are displayed in Figures 3 through 8. These figures display the responses of macroeconomic and term structure variables to each of the identified macro shocks. In addition, Figures 4, 6, and 8 display the "inflation level", "inflation slope", "real rate level", and the "real rate slope" (rows 2, 5, 3, and 6, respectively). The former two weight the responses of one-month-, 12-month-, and 60-month-ahead inflation expectations by the same eigenvector elements, displayed in the first two rows of Table 2, that we used to construct the yield level and yield slope, respectively. For example, the inflation level can be written in an analogous fashion to (5):

$$\pi_t^{level} = \alpha_1\ \pi_t^1 + \alpha_{12}\ \pi_t^{12} + \alpha_{60}\ \pi_t^{60}$$

where π_t^m is the m-month ahead inflation expectation. The real rate level is simply the yield level minus the inflation level. The slope variables are defined analogously for the eigenvector weights associated with the second largest eigenvalue. These four plots thus decompose movements in the yield level and slope into the component due to the response of real rates[21] and the component due to expected inflation.[22] Finally, the last two rows of Figures 4, 6, and 8 display the responses of the 12-month and 60-month term premiums. These are the responses of the 12- and 60-month yields in excess of that predicted by the expectations hypothesis. For the 12-month term premium TP_t^{12}, this is

$$TP_t^{12} = y_t^{12} - \frac{1}{12}\sum_{s=0}^{11} E_t\left[y_{t+s}^1\right].$$

The 60-month term premium is defined analogously.

The dashed lines in these figures give 90% probability error bands for the impulse responses, computed using 500 Monte Carlo draws from the posterior distribution of the model's parameters. For the Galí and single-shock identifications, these probability bands are computed by taking Monte Carlo draws from the Bayesian posterior distribution computed using the methods described in Sims and Zha (1999), Zha (1999), and Waggoner and Zha (2003). For the baseline identification and its variants (described in section 5.6), we compute the posterior distribution using the approach described in Evans and Marshall (2002), which extends these Bayesian methods in a natural way to account for uncertainty

[21] Throughout this paper, the term "real rate" refers to the real return to a nominally risk-free bond.

[22] To conserve space we do not display the term structure curvature or its components. The reason is that, with our principal components decomposition, the term structure curvature is the residual after level and slope are removed. The response of this residual to macroeconomic shocks is small and insignificant in almost all the experiments we conduct.

in regression (7).[23] Finally, Table 5 displays the decomposition of the variance of the one- and 5-year ahead macroeconomic forecast errors implied by the ε^{Base} vector of shocks, also with 90% probability error bands.

7.1. Responses to the MRS shock and the IS shock

The first columns of Figures 3 and 4 give the responses to the ε_{MRS}^{Base} shock. The shock in the Galí model most closely associated with the MRS shock is the IS shock, which we display in the second column. The third column displays responses of $\varepsilon_{MRS}^{Single}$. The responses of output, inflation, bond yields, and the Federal funds rate to ε_{MRS}^{Base} and $\varepsilon_{IS}^{Galí}$ are qualitatively quite similar. This is striking, since $\varepsilon_{IS}^{Galí}$ is derived using a very different identification strategy from ε_{MRS}^{Base}. The effects of ε_{MRS}^{Base}, $\varepsilon_{IS}^{Galí}$, and $\varepsilon_{MRS}^{Single}$ on output and inflation are displayed in the first two rows of Figure 3. Upon impact, real GDP rises immediately with a persistent effect that lasts several years. The fraction of output variance accounted for by ε_{MRS}^{Base} is 39% at the 5-year horizon in Table 5. GDP also rises in response to $\varepsilon_{MRS}^{Single}$, but the response is somewhat less pronounced and persistent than for the other two shocks. Inflation rises for each of the identified shocks, but their timing and magnitudes differ, as well as the precision of their estimated effects. Across the three measures, there is substantial probability that inflation remains positive for one year. The ε_{MRS}^{Base} and $\varepsilon_{IS}^{Galí}$ shocks have a more lasting effect on inflation. The transitory nature of the inflation response indicates that the MRS shock contributes only a small piece of the total price level variation. According to Table 5, the fraction of inflation variation accounted for by ε_{MRS}^{Base} is only 9% at the 5-year horizon.

Consider now the policy response to ε_{MRS}^{Base}, $\varepsilon_{IS}^{Galí}$, and $\varepsilon_{MRS}^{Single}$. All three identifications imply that the systematic component of monetary policy responds with a persistent and significant increase in the nominal funds rate. The Taylor (1993) principle is evident in the two model-based responses: the real funds rate rises in response to a shock that increases both deviations of output and inflation from their target levels. Table 5 indicates that ε_{MRS}^{Base} is an important driver of systematic monetary policy, accounting for 34% of the 5-year ahead variance of the Federal funds rate. Together, these results depict shocks that shift the aggregate economy's demand for goods and services, and that the Fed responds to by "leaning against the wind."

The responses of yields and yield curve components to the MRS and IS shocks are displayed in rows 6 - 8 of Figure 3 and in Figure 4. Three sets of results are particularly

[23] Because this system is overidentified, the standard Bayesian procedure (Doan, 2000) is inappropriate. (See Sims and Zha, 1999). In our analysis, matrix D in equation (15) is estimated by maximum likelihood for each Monte Carlo draw. Sims and Zha (1999) refer to this as the "naive Bayesian procedure". We are currently investigating how to modify Sims and Zha's (1999) approach to overidentified systems for our framework .

noteworthy. First, each of the three shocks ε_{MRS}^{Base}, $\varepsilon_{IS}^{Galí}$, and $\varepsilon_{MRS}^{Single}$ have substantial, persistent and significant effects on individual nominal yields. For expansionary MRS shocks, yield responses are large, positive, persistent and have large posterior probabilities of being non-zero. For example, following a one-standard deviation positive ε_{MRS}^{Base} shock, the three yields increase between 25 and 38 basis points on impact. These responses are long-lived, remaining well above zero over four years after the initial impulse. These responses indicate that aggregate demand shocks lead to substantial variation in nominal yields. According to Table 5, the ε_{MRS}^{Base} accounts for 37%, 37%, and 26% of the the one-month, 12-month, and 60–month yield variance at the 5-year horizon.

Second, owing to the similar responses across the maturity spectrum following these shocks, the level of the yield curve increases with little change in the slope. (See Figure 4, rows 1 and 4.) The reason for this pronounced response of the yield curve level is that all three shocks, ε_{MRS}^{Base}, $\varepsilon_{IS}^{Galí}$, and $\varepsilon_{MRS}^{Single}$, shift inflation and real rates in the same direction. Consider for example the ε_{MRS}^{Base} shock. The inflation level response (Figure 4, row 2) is initially positive and rises to 18 basis points one year after a positive impulse with substantial posterior probability. The response of the real rate level (row 3) peaks at 33 basis points one quarter following the impulse, decaying gradually. These two components reinforce each other, resulting in the significant yield level response. Similar complementary patterns obtain for $\varepsilon_{IS}^{Galí}$ and $\varepsilon_{MRS}^{Single}$. The pronounced real rate responses following both MRS shocks are consistent with our interpretation that these are transitory shocks to the marginal utility of consumption.

Third, the large and persistent responses of longer-term interest rates to the MRS and IS shocks are due in part to another factor: the significant and persistent response of term premiums. In the last two rows of Figure 4, we plot the responses of the 12-month and 60-month term premium. For all three shocks, ε_{MRS}^{Base}, $\varepsilon_{IS}^{Galí}$, and $\varepsilon_{MRS}^{Single}$, there is an economically significant increase in both of these term premiums. The term premium responses to $\varepsilon_{MRS}^{Single}$ peak 3 quarters after the impulse at 21 and 29 basis points for the 12- and 60-month premium, respectively. A similar, though smaller, response pattern can be seen for the ε_{MRS}^{Base} and $\varepsilon_{IS}^{Galí}$ shocks. For each of these shocks, the error bands place a large probability on positive term premium responses both at the 9 to 12 month horizon and the 3 to 4 year horizon. One can interpret these term premium responses as evidence that the market price of risk increases in response to an IS or MRS shock.

Notice that the peaks in the term premiums are mirrored in the responses of the yields themselves. These term premium responses account for about one-half of the total response of these longer yields. Equivalently, the average of the one-month rates only account for one half of long yield responses. While the magnitude of the term premium responses to the

Galí IS shock are small, they do induce sufficient additional movement in the longer yields to keep the response of the term slope flat. If these term premium responses were set to zero, the slope of the term structure would fall significantly over the four years following a positive IS shock, and much of the movement in the yield curve would be attributed to the slope, rather than the level.

Finally, the identification for ε_{MRS}^{Base} depends on the identifying restrictions given in equation (15), where the MRS and monetary policy shock measures are assumed to be relatively clean but the technology measure is allowed to be confounded with ε_{MRS} and ε_{MP}. However, the qualitative properties of the responses to ε_{MRS} remain even under alternative identifications (16) and (17).[24] In particular, under identification (16) the responses of output and inflation to ε_{MRS}^{Alt} are both positive. The output response is smaller in magnitude and less persistent than in the baseline case, but the inflation response is somewhat larger. Overall, the yield responses under identification (16) are significantly positive, comparable in magnitude to the baseline case, and, if anything, somewhat more persistent. Identification (17) is also qualitatively similar to the baseline model. As with identification (16), the output response is weaker than in the baseline case; the yield responses on impact are larger than in the baseline case, but they decay somewhat faster. On the whole, we conclude that the implications of the MRS shock for both macro variables and yields are fairly robust across alternative identifications.

7.2. Responses to the technology shock and the supply shock

The first column in Figures 5 and 6 shows responses to $\varepsilon_{Tech}^{Base}$, the technology shock derived from the Basu-Fernald-Shapiro technology measure. Since the shock in the Galí model most closely associated with a technology shock is the supply shock, $\varepsilon_{Supply}^{Galí}$, we give the responses to this shock in the second column of these figures. The third column gives the responses to $\varepsilon_{Tech}^{Single}$. The rows in Figures 5 and 6 are analogous to those in figures 3 and 4.

Consider first the responses to $\varepsilon_{Tech}^{Base}$ and $\varepsilon_{Supply}^{Galí}$. The responses of output, inflation, bond yields, and the Federal funds rate to $\varepsilon_{Tech}^{Base}$ are quite similar to the responses to the Galí supply shock. As with ε_{MRS}^{Base} and $\varepsilon_{IS}^{Galí}$ the similarity between these very different identification approaches is noteworthy. In particular, both the Galí supply shock and the $\varepsilon_{Tech}^{Base}$ induce an increase in output, a fall in the inflation rate, and a decline in all three bond yields. The response of output to both shocks is pronounced and long-lived after about 5 quarters, but the initial output response is negligible. This delayed response to a technology

[24] To conserve space, we do not display the impulse responses under these alternative identifying assumptions. Detailed plots of these responses can be obtained from the authors upon request.

shock is consistent with several recent empirical and theoretical analyses.[25] As a result of this response pattern, the $\varepsilon_{Tech}^{Base}$ shock accounts for only 1% of the one-quarter ahead variance of output, but 20% of the five-year ahead variance. (See Table 5.)

Both $\varepsilon_{Supply}^{Galí}$ and $\varepsilon_{Tech}^{Base}$ induce a pronounced short-run decline in the one-month-ahead inflation rate. The largest decline in inflation in response to the Galí supply shock is a 75 basis point decline, one month after the impulse. The largest decline in response to $\varepsilon_{Tech}^{Base}$ is a 55 basis point decline, three quarters after the impulse. These inflation responses are transitory, dissipating over the next three to four years. According to Table 5, the $\varepsilon_{Tech}^{Base}$ shock accounts for 55% of the 5-year ahead variance of the inflation rate. The inflation responses are consistent with an economy in which falling marginal costs lead to smaller price increases.

Both $\varepsilon_{Tech}^{Base}$ and the Galí supply shock induce pronounced, persistent, and significant declines in nominal yields of all maturities. For $\varepsilon_{Tech}^{Base}$, the responses to a one-standard deviation shock bottom out in three to four quarters at -43, -47, and -38 basis points for the 1-, 12-, and 60-month yields respectively. The impulse responses to the Galí supply shock are somewhat smaller, but the longer yields continue to fall for about two years, with a maximal response of -27 and -24 basis points for the 12- and 60-month yields, respectively. Overall, $\varepsilon_{Tech}^{Base}$ accounts for 39%, 46%, and 57% of the one-month, 12-month, and 60-month yield variance at the 5-year horizon. Since these negative responses of the three yields are similar in magnitude, the level of the yield curve falls significantly. This decline is economically important: a one-standard deviation shock to either $\varepsilon_{Tech}^{Base}$ or $\varepsilon_{Supply}^{Galí}$ induces approximately a 30 basis point decline in the yield level. (In contrast, the effect on the yield slope is small and insignificant.)

Again, it is useful to decompose these responses of nominal yields into their expected inflation and real-rate components. The initial responses of the real rate to these shocks are positive, as one would expect from a positive impulse to the marginal product of capital. However, the large deflationary impact of these shocks overwhelms the contribution of the real rate, hence the negative initial responses of nominal interest rates. Interestingly, the initial positive response of the real rate turns negative within three to five quarters, so the real rate response actually serves to prolong the negative response of nominal rates. A key factor driving this reversal is the systematic response of monetary policy. In response to either $\varepsilon_{Tech}^{Base}$ or $\varepsilon_{suppy}^{Galí}$, the monetary authority reduces the nominal Federal funds rate by a total of nearly 70 basis points over the three quarters following (the fourth row of Figure 5).

[25] Galí (1999) and Basu, Fernald and Kimball(2000) interpret the delayed response of output to technology shocks as evidence of inertial aggregate demand due to price stickiness. In Boldrin, Christiano, and Fisher (2001) and Francis and Ramey (2001), this delay is consistent with inertial aggregate demand due to habit persistence in consumption and investment adjustment costs.

This monetary policy response is quite persistent. According to Table 5, $\varepsilon^{Base}_{Tech}$ accounts for 46% of the 5-year ahead variance of the Federal funds rate. This response is consistent with the literature on Taylor (1993) rules: $\varepsilon^{Base}_{Tech}$ and $\varepsilon^{Galí}_{suppy}$ move inflationary expectations below the target inflation rate and reduce (or leave unchanged) the output gap.[26] Note that after the first two quarters the funds rate response exceeds the inflation response. Consequently, the real Federal funds rate falls. This decline in the real funds rate is consistent with the stability condition of the Taylor rule literature, that the nominal interest rate respond more than one-for-one with inflation. Together, these results imply a persistent fall in short-term real rates that acts as an additional force reducing the level of the nominal yield curve.

An additional factor that shifts the level of the yield curve is the response of term premiums. According to the last two rows of Figure 6, there is substantial probability that the $\varepsilon^{Base}_{Tech}$ and $\varepsilon^{Galí}_{suppy}$ shocks induce an increase in the five year term premium over the first six months, with a subsequent decline after three years. Notice that the real rate level response mimics the response of the five year term premium. If this term premium response were flat, the real-rate response would be shorter-lived. Together, the monetary policy's reduction in the Federal funds rate and the negative term premiums three to four years after impact tend to pull the level of the real yield curve down. Furthermore, the response of the 5-year term premium to $\varepsilon^{Base}_{Tech}$ is large enough to induce a pronounced flattening of the real term structure slope. (See Figure 6, row 6.)

While $\varepsilon^{Base}_{Tech}$ and $\varepsilon^{Galí}_{suppy}$ induce a persistent expansion of output along with pronounced decline in the inflation and bond yields, the single-shock technology identification $\varepsilon^{Single}_{Tech}$ induces rather different response patterns. These are displayed in the third columns of Figure 5 and 6. In particular, $\varepsilon^{Single}_{Tech}$ induces only a transient expansion of output, and a small and transient drop in the inflation rate. Because the inflation response is so small, it fails to outweigh the real rate response, so the responses of the three bond yields are actually positive, although small and of dubious significance. (Note that the error bands straddle the zero response.) As a result, the responses of the yield level and its inflation and real-rate components are positive but small. Furthermore, the response of the real rate is short-lived, dissipating in one quarter, and the response of monetary policy is negligible.

These small responses to a technology measure are somewhat surprising. One interpretation of these results is that the single-shock identification strategy recovers a purely transitory technology improvement. However, another interpretation is that $\varepsilon^{Single}_{Tech}$ is contaminated with non-technology shocks. Suppose that the procedure for constructing the

[26] The sign of the output gap turns on whether potential output rises immediately with the expansionary technology shock (as in Galí, 1999 and Basu, Fernald, and Kimball, 2000) or is delayed due to adjustment costs and habit persistence (as in Boldrin, Christiano, and Fisher, 2001, and Francis and Ramey, 2001).

model-based technology measure η_{Tech} fails to remove all influence of the underlying MRS and monetary policy shocks. This could be the case if an MRS shock affects capital utilization, labor hoarding, or industrial composition, and the Basu-Fernald-Shapiro procedure only imperfectly controls for these effects. Recall that the specification for D in equation (15) purges $\varepsilon_{Tech}^{Base}$ of any remaining contamination from the MRS and monetary policy shocks. However, the method used to generate $\varepsilon_{Tech}^{Single}$ fails to do so. The $\varepsilon_{Tech}^{Single}$ shock would then actually be a combination of ε_{Tech}, ε_{MRS}, and ε_{MP}. Since an expansionary MRS shock moves inflation in the opposite direction to an expansionary technology shock, this contamination would tend to attenuate the inflation response to $\varepsilon_{Tech}^{Single}$. As we have seen, the strong yield responses to $\varepsilon_{Tech}^{Base}$ are primarily driven by this inflation response, so it is entirely possible that this attenuation of the inflation response effectively wipes out the yield responses as well.

In this event, we should see a similarly contaminated response pattern following an ε_{Tech} shock when the technology shock is identified using the restrictions in equations (16) or (17). (Note that the implications of (16) and (17) for ε_{Tech}^{Alt} are identical.) When we consider these alternative identifications, we indeed find that the inflation and yield responses resemble the corresponding response to $\varepsilon_{Tech}^{Single}$.[27] The responses of the macro variables are qualitative the same as those for $\varepsilon_{Tech}^{Single}$, except that the responses to ε_{Tech}^{Alt} are somewhat larger in magnitude. As with $\varepsilon_{Tech}^{Single}$, the inflation response to ε_{Tech}^{Alt} is of dubious significance, since the error bands straddle the zero response. While the yield responses to $\varepsilon_{Tech}^{Base}$ were negative, reflecting the strong negative inflation responses, the initial yield responses to ε_{Tech}^{Alt} are actually positive. As with $\varepsilon_{Tech}^{Single}$, these positive responses result from the small and insignificant inflation response combined with a positive real-rate response. Unlike $\varepsilon_{Tech}^{Single}$, the initial yield responses to ε_{Tech}^{Alt} appear to be positive with high probability, since the lower error band initially exceeds the zero response. However, the magnitudes are small (between 20 and 25 bp) and they dissipate rapidly, with the lower error band crossing the zero response in about three quarters. The resulting yield level responses are small and transitory. On the whole, these small inflation and yield responses are consistent with the explanation that η_{Tech} is sufficiently contaminated by the MRS shock to attenuate the price response to technology impulses.

7.3. Responses to the fiscal shock

Another fundamental macroeconomic impulse comes from exogenous shifts in fiscal policy. The responses to $\varepsilon_{Fiscal}^{Base}$ and $\varepsilon_{Fiscal}^{Single}$ are displayed in the first two columns of Figures 7 and 8. First, note that output responds positively to $\varepsilon_{Fiscal}^{Single}$ upon impact. The overall appearance

[27] These impulse responses using the alternative identifications are available from the authors upon request.

of this output response is qualitatively similar to the response obtained by Blanchard and Perotti to their government spending shock, although our error bands are somewhat wider. Second, considering the low R^2 in the regression of the VAR innovations u_t onto the model-based measures η_t, it is not surprising that the uncertainty bands for the $\varepsilon^{Base}_{Fiscal}$ impulse responses are large.

Turning to the yields, we do not find a significant response of interest rates to the fiscal policy shock under either model-based identification. The point estimates of the yield responses in columns 1 and 2 of Figure 7 are small, and the error bands straddle the zero response. These small effects on the yield curve may be due to the transitory effect of the Blanchard-Perotti fiscal shock measures on economic activity and on overall measures of fiscal debt.

As an alternative exploration of the possible non-Ricardian influence of fiscal shocks on the nominal yield curve, we consider Ramey and Shapiro's (1998) identification of exogenous military build-ups. Ramey and Shapiro identify three post-World War II episodes of military spending increases that were due to exogenous events. These episodes correspond to the onset of the Korean War (third quarter of 1950), the Vietnam War (first quarter of 1965) and the Carter-Reagan military expansion (first quarter of 1980). Let RS_t correspond to a dummy variable that takes the value of one on each Ramey-Shapiro episode date, and zero otherwise. Let $\widetilde{Z}_t$ denote the vector of macroeconomic and financial data that includes real GDP, the GDP chain-price index, PCOM, the government budget surplus as a percent of GDP, 1-month yield, 12-month yield and 60-month yield. We include the government budget surplus to assess the plausibility of the Ramey-Shapiro impulses for our system. We do not include the Federal funds rate in $\widetilde{Z}_t$ because a well-developed Federal funds rate market did not exist during the early part of our sample. We estimate the following VAR[28]

$$\widetilde{Z}_t = \alpha_0 + \alpha_1 t + \alpha_2 t \cdot 1_{\{t \geq 1973:Q2\}} + A(L)\widetilde{Z}_{t-1} + \beta(L)RS_t + u_t$$

where $1_{\{\cdot\}}$ is the indicator function. We follow Ramey and Shapiro (1998) in allowing for a trend break at 1973:Q2. We use data from 1948:Q2 - 2000:Q1. Four lags are incorporated in the VAR. We then compute the responses to a unit Ramey-Shapiro episode. Column 3 of Figures 7 and 8 display the results of this exercise.

There are four results from this experiment we would like to highlight. First, our macro variable responses are similar to the findings of Ramey and Shapiro (1998) and Burnside,

[28] We follow Burnside, Eichenbaum, and Fisher (1999) in estimating a VAR system for the vector Z_t. Ramey and Shapiro (1998) simply estimate univariate systems for each variable of interest. Burnside, Eichenbaum and Fisher, however, allow for different intensities of the Ramey-Shapiro episodes. With only three episodes and substantial uncertainty at the beginning of each Ramey-Shapiro episode regarding the eventual increase in military purchases, we follow Ramey and Shapiro (1998) in giving equal weight to each episode.

Eichenbaum, and Fisher (1999). Real GDP increases with a two-quarter delay, peaking in the second year following the onset of the episode. The price level jumps on impact, and there is a considerable inflation response in the initial two quarters. Second, we find that the real fiscal surplus actually increases as a percentage of real GDP for the first two years following the onset of a Ramey-Shapiro episode. Neither Ramey and Shapiro (1998) nor Burnside, Eichenbaum, and Fisher (1999) investigate the response of the fiscal surplus. However, Burnside, Eichenbaum, and Fisher (1999) find that average capital tax rates increase following a Ramey-Shapiro episode. With the estimated delay in government purchases, the increase in tax revenues seems to push the government budget into surplus initially.

Third, the Ramey-Shapiro fiscal shocks result in large responses in all three yields, peaking six quarters after the impulse. These results are in striking contrast to the small responses elicited by the Blanchard-Perotti measures $\varepsilon_{Fiscal}^{Single}$ and $\varepsilon_{Fiscal}^{Base}$. The error bands imply substantial probability that the responses of the 1- and 12-month yields to the Ramey-Shapiro shocks are positive. (The error bands are somewhat wider for the 5-year yield.) Unlike the Blanchard-Perotti measures, the Ramey-Shapiro fiscal shocks shift the level of both the nominal and real yield curves. These level responses are quite persistent.

Fourth, these interest rate responses appear to be driven in part by systematic monetary policy. Initially, the increased fiscal surplus drives down the one-month real interest rate. However, the increases in output and inflation elicit an offsetting response of monetary policy. With output and inflation rising above their target levels, the Taylor principle calls for an increase in short-term real interest rates. This seems to be the dominant effect on the one-month nominal and real yield after the first few quarters.

To summarize, the evidence on the response of interest rates to fiscal policy shocks is mixed. In our system, the Blanchard-Perotti measures of fiscal shocks induce at best a short-lived response of output and inflation, resulting in negligible interest rate responses. In contrast, there is much stronger evidence in favor of fiscal policy effects on interest rates when the Ramey-Shapiro measures are used. Apparently, the Ramey-Shapiro fiscal shocks represent different, larger, and more persistent fiscal shocks than the Blanchard-Perotti measures.

8. Conclusion

This paper has found robust empirical evidence that macroeconomic factors account for most of the movement in nominal Treasury yields of maturities ranging from one month through five years. Technology shocks and shocks to the marginal rate of substitution between consumption and leisure strongly influence the level of the yield curve. A variety of analyses support these conclusions: an atheoretical VAR data exploration, Galí's (1992) structural VAR identification, and a new identification approach from model-based measures of economic shocks. We repeatedly found that aggregate demand-like shocks that increase real GDP and prices together have substantial level effects. By jointly increasing real interest rate levels and inflation levels, these effects reinforced the overall contribution to the level of the nominal yield curve. Our measures of technology shocks also lead to nominal yield curve level effects. However, these shocks produce competing influences: positive shocks increase real GDP and real interest rates but lower inflation. The overall transmission to nominal yields is attenuated by these contrasting influences, but the effect is still quite large, with the inflation level effect playing the dominant role.

Our results differ from those of Ang and Piazzesi (2001), who find little response of the yield curve level to macroeconomic impulses. A key difference between our approach and that of Ang and Piazzesi (2001) is that we allow macroeconomic shocks to feed back on the real economy through the monetary transmission mechanism. The role of systematic monetary policy is critical for understanding the way macro impulses jointly affect interest rates and the real economy. The Taylor principle seems to be a feature of these empirical responses: if inflationary expectations rise above the inflation target, the Federal funds rate increases by more than the inflation gap. In addition, the funds rate rises in response to real GDP above its potential level. Our macroeconomic shocks induce changes in output and inflation gaps, and systematic monetary policy adjusts the funds rate accordingly. Long term interest rates move in anticipation of these systematic policy responses.

We also found evidence that term premiums respond to impulses affecting both aggregate demand and supply. Changes in term premiums are associated with time-variation in the market price of risk. Consistent implications for term premium responses across shock measures may help macroeconomists and financial economists further integrate macroeconomic facts into asset-pricing models. More generally, by matching our economic factors with the latent factors that have been the focus of much of the term structure literature in empirical finance, it should be possible to further integrate this literature into the analysis of dynamic general equilibrium models.

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Table 1: Fraction of Yield Variance Attributable to Macro Shocks under Recursive Orthogonalization

Panel A: One-Month Yield

Steps ahead:	1-month	12-months	60-months
ε_Y	0.029 (0.012,0.054)	0.218 (0.116,0.329)	0.263 (0.083,0.495)
ε_{PCOM}	0.013 (0.000,0.055)	0.328 (0.189,0.452)	0.467 (0.240,0.647)
ε_P	0.011 (0.000,0.067)	0.019 (0.009,0.095)	0.066 (0.014,0.268)
ε_{FF}	0.271 (0.200,0.317)	0.250 (0.159,0.321)	0.117 (0.064,0.202)

Panel B: 12-Month Yield

Steps ahead:	1-month	12-months	60-months
ε_Y	0.071 (0.045,0.107)	0.235 (0.110,0.366)	0.260 (0.077,0.522)
ε_{PCOM}	0.041 (0.008,0.100)	0.379 (0.218,0.501)	0.518 (0.273,0.684)
ε_P	0.004 (0.000,0.044)	0.020 (0.006,0.094)	0.073 (0.011,0.282)
ε_{FF}	0.237 (0.172,0.286)	0.146 (0.081,0.231)	0.069 (0.035,0.161)

Panel C: 60-Month Yield

Steps ahead:	1-month	12-months	60-months
ε_Y	0.058 (0.019,0.117)	0.189 (0.045,0.357)	0.189 (0.032,0.443)
ε_{PCOM}	0.052 (0.009,0.117)	0.340 (0.124,0.475)	0.535 (0.218,0.666)
ε_P	0.005 (0.000,0.046)	0.029 (0.009,0.135)	0.119 (0.014,0.358)
ε_{FF}	0.085 (0.027,0.154)	0.064 (0.020,0.193)	0.048 (0.017,0.180)

ε_Y, ε_{PCOM},ε_P, and ε_{FF} denote the orthogonalized residuals to industrial production, commodity price index, the price level, and the Federal funds rate. Numbers in parentheses are lower and upper 90% error bands, computed using 500 Monte Carlo draws from the Bayesian posterior distribution of the model parameters.

Table 2: Weights Used to Construct Yield Curve Level, Slope, and Curvature

	One-month yield	12-month yield	60-month yield
Level	0.5709	0.6764	0.4653
Slope	-0.6019	-0.0408	0.7976
Curvature	0.5585	-0.7354	0.3839

The time series for the vector process consisting of the one-, 12-, and 60-month zero coupon yields are decomposed into 3 principal components. The level, slope, and curvature of the yield curve are identified as the first, second, and third principal components, respectively. The weights reported in this table for level, slope, and curvature are the eigenvectors associated with the largest, second largest, and smallest eigenvalues of the moment matrix of the vector of yields.

Table 3: Correlation Matrix of $\{\eta_{MP}, \eta_{MRS}, \eta_{Tech}, \eta_{Fiscal}\}$

	η_{MP}	η_{MRS}	η_{Tech}	η_{Fiscal}
η_{MP}	1.0			
η_{MRS}	0.11	1.0		
η_{Tech}	-0.11	0.05	1.0	
η_{fiscal}	-0.02	0.15	0.31	1.0

The model-based shocks to monetary policy, preferences, technology, and fiscal policy are denoted η_{MP}, η_{MRS}, η_{Tech}, and η_{fiscal}, respectively. The derivation of these shocks is described in section 5.

Table 4: R^2 **Estimates in Regressions of Model-Based Shocks on VAR Residuals**

Shock	R^2
η_{MP}	66.0%
η_{MRS}	22.7%
η_{Tech}	36.7%
η_{fiscal}	8.7%

This table displays the R^2s from the regression of each of the model-based shocks $\{\eta_{MP}, \eta_{MRS}, \eta_{Tech}, \eta_{Fiscal}\}$ on the VAR residuals u_t, as in equation (7).

Table 5: Variance Decomposition using Baseline Shock Measures

Panel A: Variance Decomposition at 1-year Horizon

	ε_{MRS}	ε_{Tech}	ε_{Fiscal}	ε_{MP}
Real GDP	65	0	0	34
	(48 - 80)	(0 - 8)	(0 - 4)	(17 - 48)
Inflation	1	47	51	1
	(1 - 17)	(7 - 82)	(7 - 83)	(1 - 28)
PCOM	10	52	20	19
	(1 - 32)	(3 - 76)	(1 - 81)	(4 - 40)
Fed Funds	34	32	1	33
	(11 - 59)	(3 - 39)	(1 - 36)	(18 - 52)
1-month yield	42	20	1	18
	(20 - 61)	(2 - 26)	(1 - 26)	(11 - 32)
12-month yield	48	25	1	8
	(24 - 67)	(2 - 33)	(1 - 32)	(5 - 20)
60-month yield	37	25	1	2
	(12 - 57)	(2 - 36)	(1 - 33)	(1 - 15)

Panel B: Variance Decomposition at 5-year Horizon

	ε_{MRS}	ε_{Tech}	ε_{Fiscal}	ε_{MP}
Real GDP	39	20	1	40
	(18 - 62)	(2 - 46)	(0 - 17)	(15 - 59)
Inflation	9	55	23	14
	(2 - 36)	(10 - 71)	(7 - 62)	(4 - 43)
PCOM	14	45	22	19
	(3 -36)	(4 - 67)	(2 - 73)	(6 - 39)
Fed Funds	34	46	4	16
	(9 - 65)	(5 - 57)	(2 - 51)	(9 - 36)
1-month yield	37	39	3	11
	(13 - 63)	(4 - 50)	(1 - 44)	(6 - 31)
12-month yield	37	46	3	6
	(12 - 66)	(4 - 57)	(1 - 52)	(3 - 25)
60-month yield	26	57	4	3
	(6 - 57)	(4 - 64)	(1 - 55)	(2 - 22)

For each of the four macro variables $\{GDP, price, PCOM, Fed\ Funds\}$ and each of the three yields, the table gives the percentage of the forecast error variance attributable to each of the four shocks $\left\{\varepsilon_{MRS}^{Base}, \varepsilon_{Tech}^{Base}, \varepsilon_{Fiscal}^{Base}, \varepsilon_{MP}^{Base}\right\}$. (Percentages for the yields do not add up to unity, due to the effects of the yield shocks γ_t in equation (1).) Panel A displays the statistics for the one-year forecast error, and Panel B displays the statistics for the 5-year forecast error. The shocks use the identification described in section 5.6. Numbers in parentheses are lower and upper 90% error bands, computed using 500 Monte Carlo draws from the Bayesian posterior distribution of the model parameters.

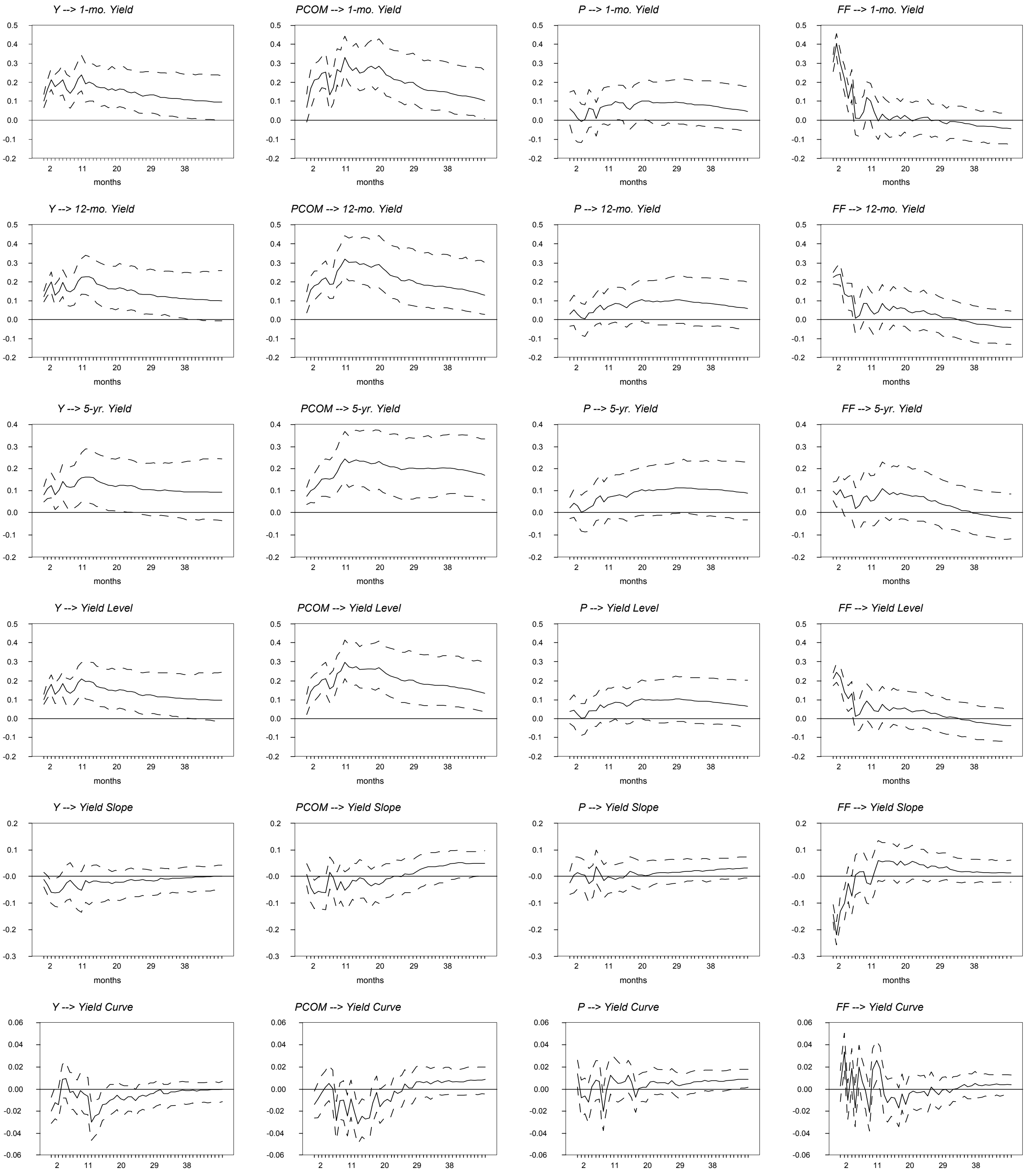

Figure 1: **Effects of Macroeconomic Variables on the Yield Curve**
Impulse response functions from recursively-orthogonalized innovations in industrial production, price level, sensitive materials prices, and the Federal funds rate. Dashed lines are Bayesian 90% probability error bands around the VAR point estimates.

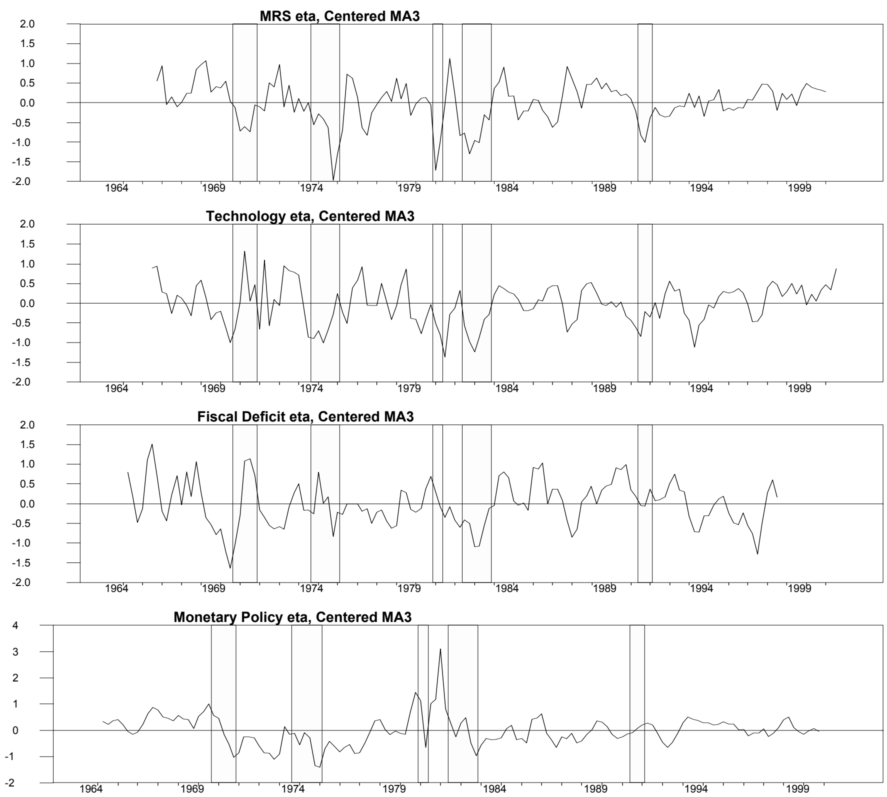

Figure 2: **Model-based shock measures**
Centered, three-quarter averages of model-based measures η_t. Shaded periods are NBER economic recessions.

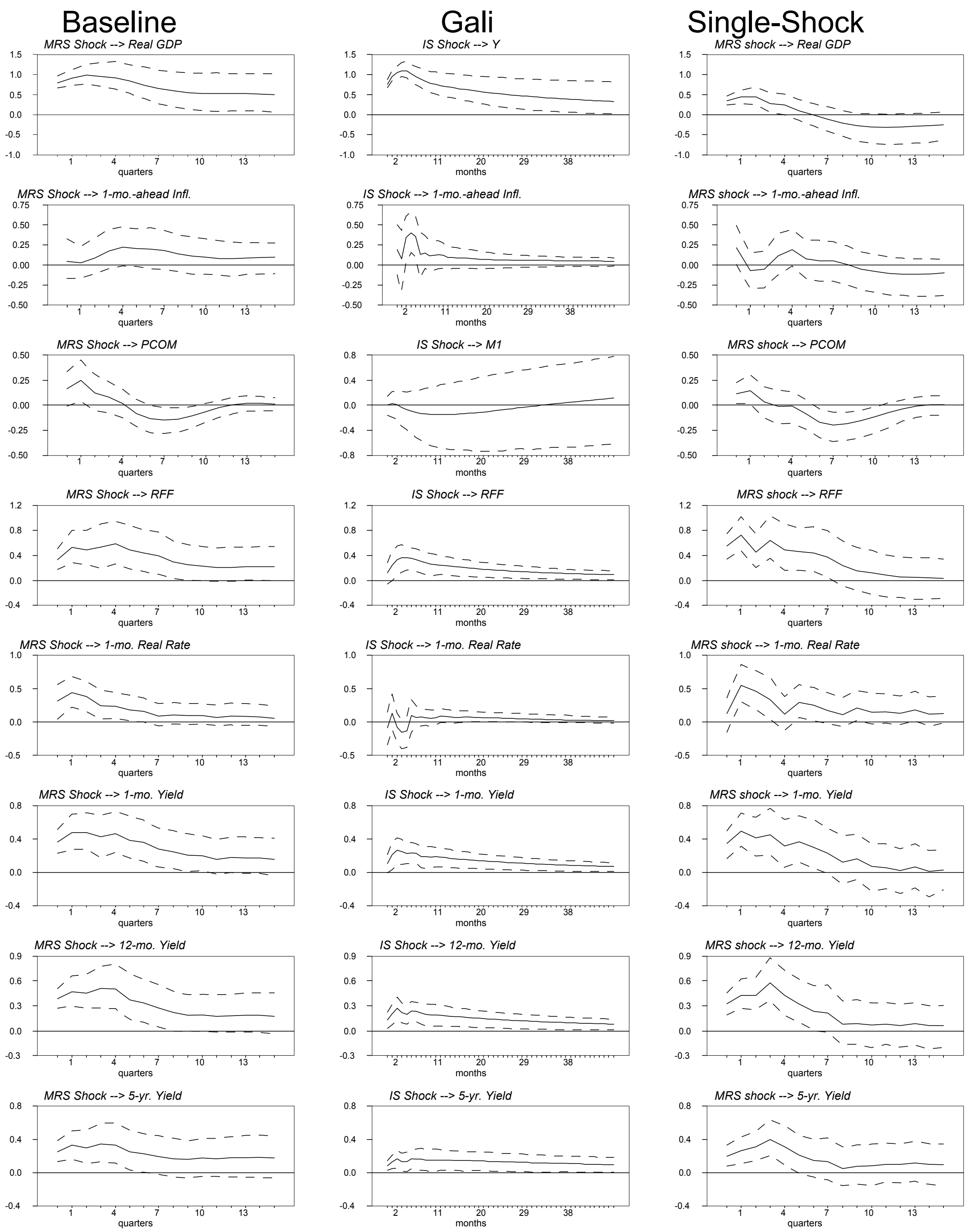

Figure 3: **IS and MRS Shock Effects on Macro Variables and Yields**
Impulse response functions following the Baseline MRS , Galí IS , and single-shock MRS impulses. Dashed lines are Bayesian 90% probability error bands around the VAR point estimates.

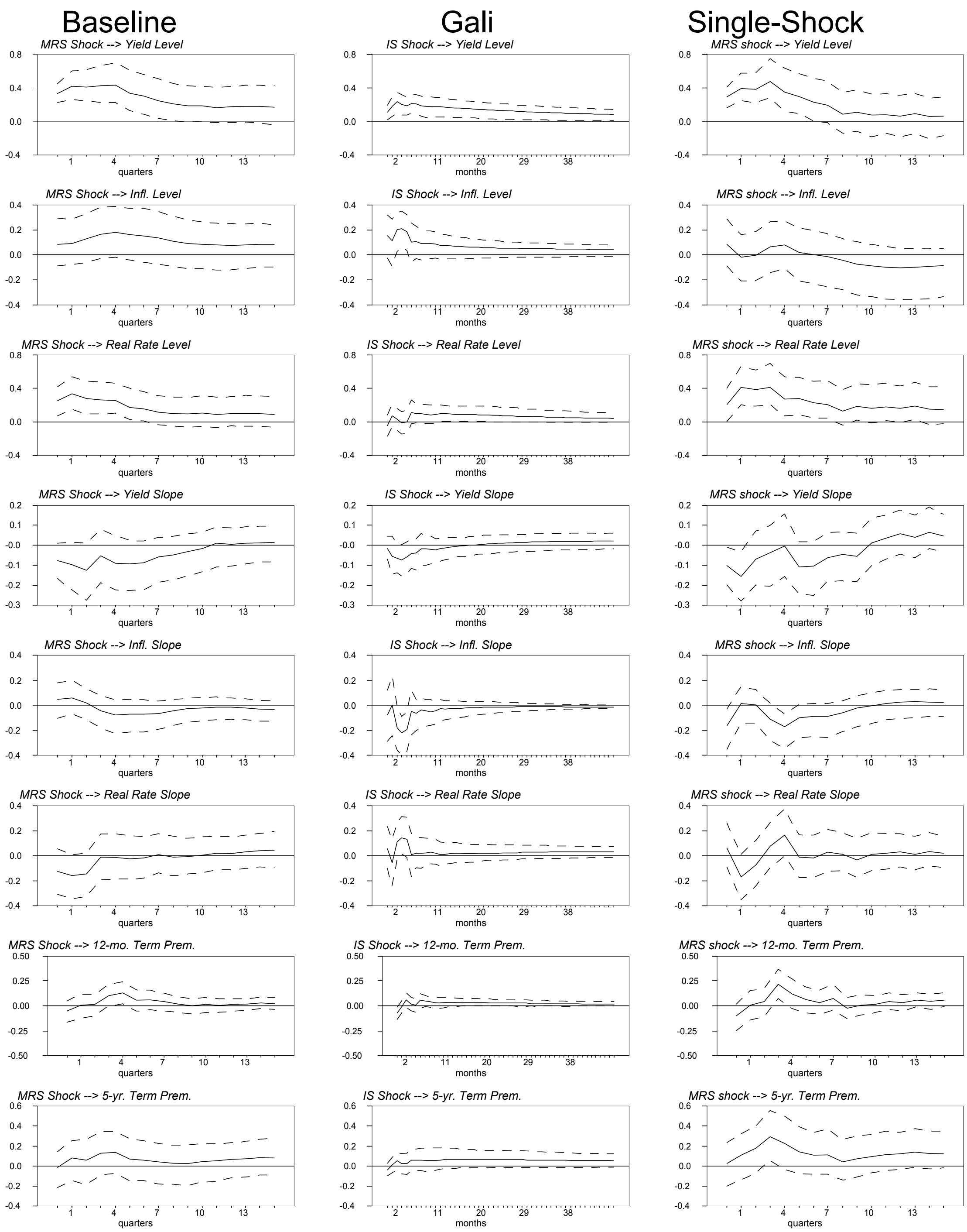

Figure 4: **IS and MRS Shock Effects on the Yield Curve**
Impulse response functions following the Baseline MRS , Galí IS , and single-shock MRS impulses. Dashed lines are Bayesian 90% probability error bands around the VAR point estimates.

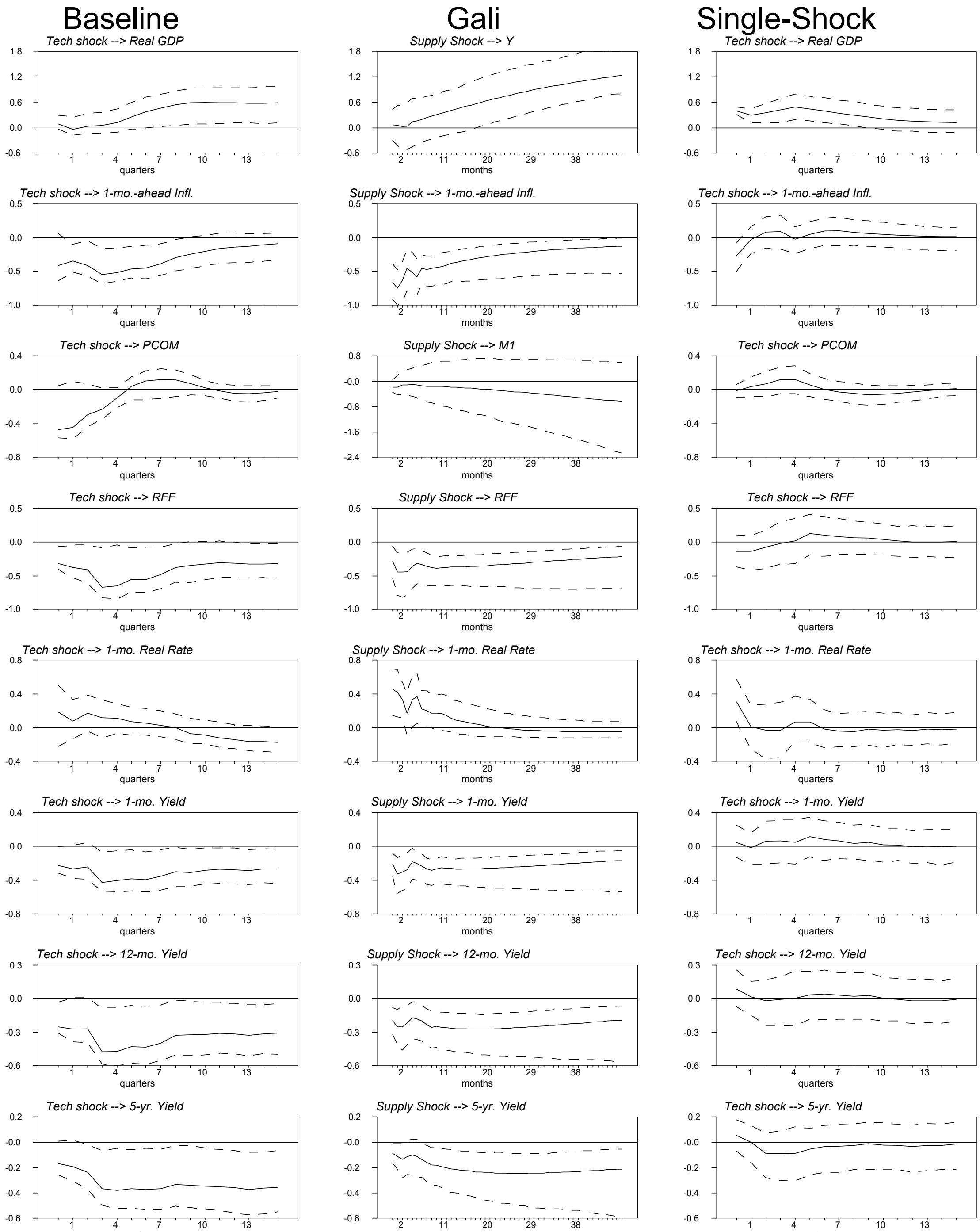

Figure 5: **Technology and Supply Shock Effects on Macro Variables and Yields**
Impulse response functions following the Baseline technology impulse , Galí IS impulse , and single-shock technology impulse. Dashed lines are Bayesian 90% probability error bands around the VAR point estimates.

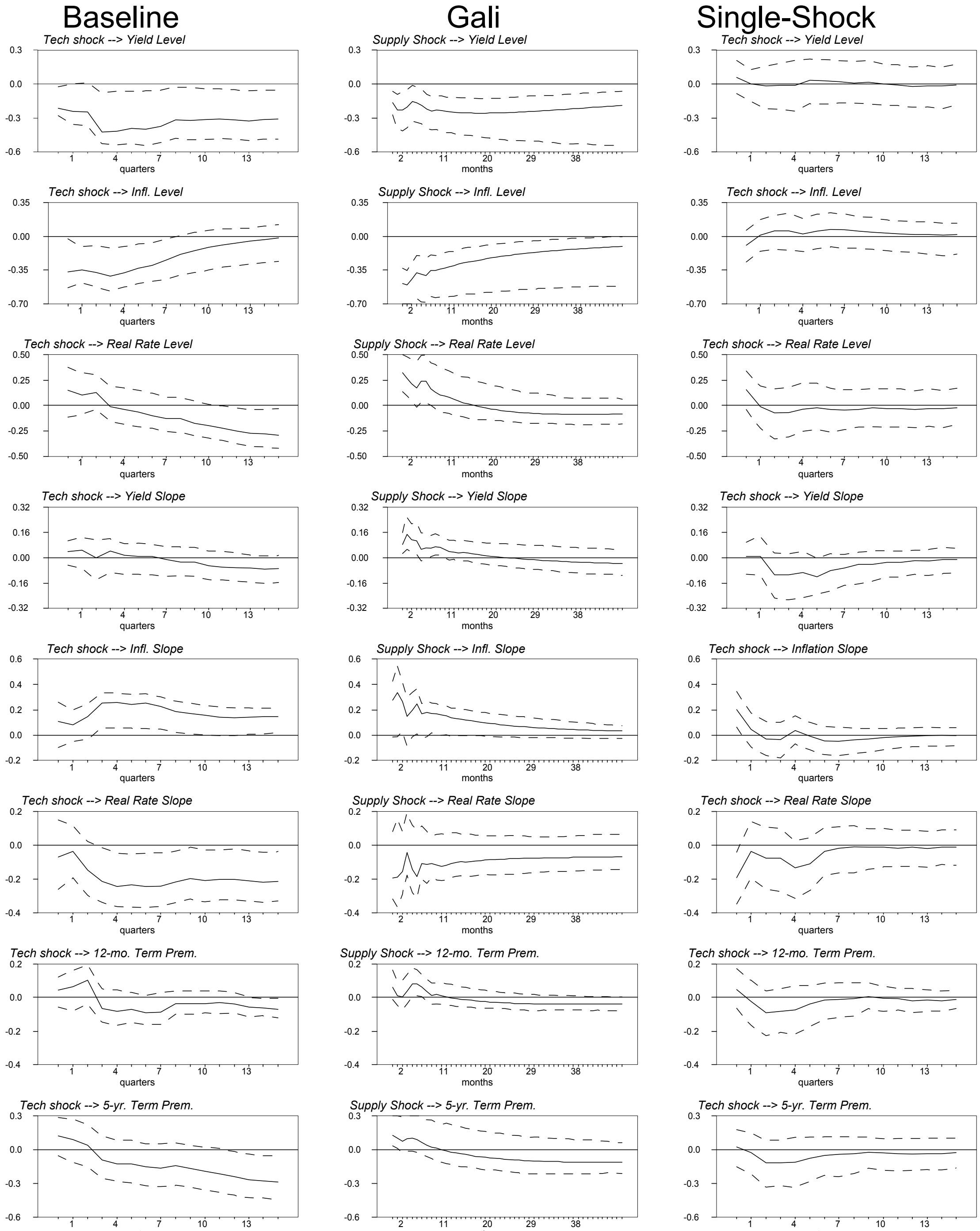

Figure 6: **Technology and Supply Shock Effects on the Yield Curve**
Impulse response functions following the Baseline technology impulse , Galí IS impulse , and single-shock technology impulse. Dashed lines are Bayesian 90% probability error bands around the VAR point estimates.

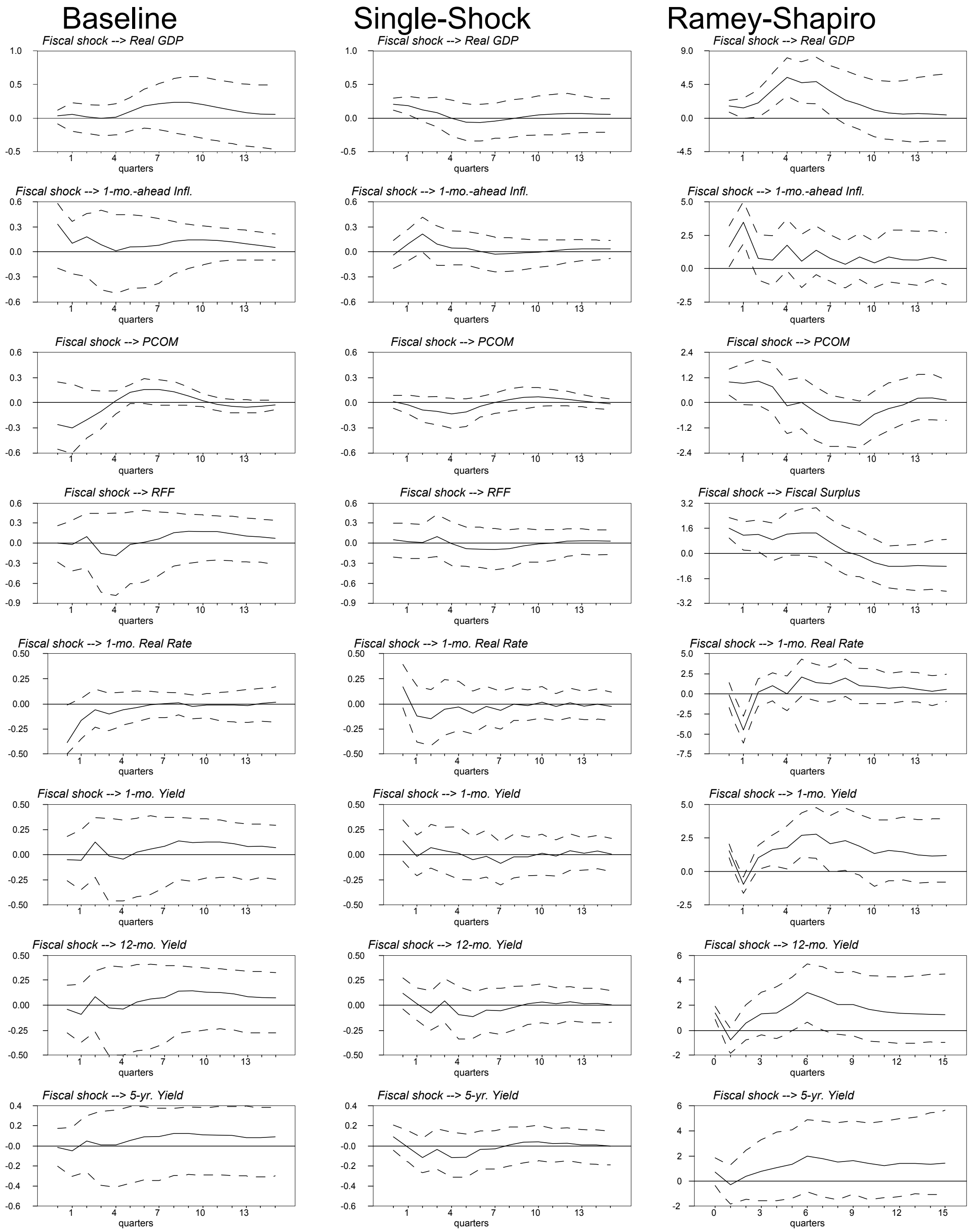

Figure 7: **Fiscal Shock Effects on Macro Variables and Yields**
Impulse response functions following the baseline and single-shock fiscal impulses, and Ramey-Shapiro military build-ups. Dashed lines are Bayesian 90% probability error bands around the VAR point estimates.

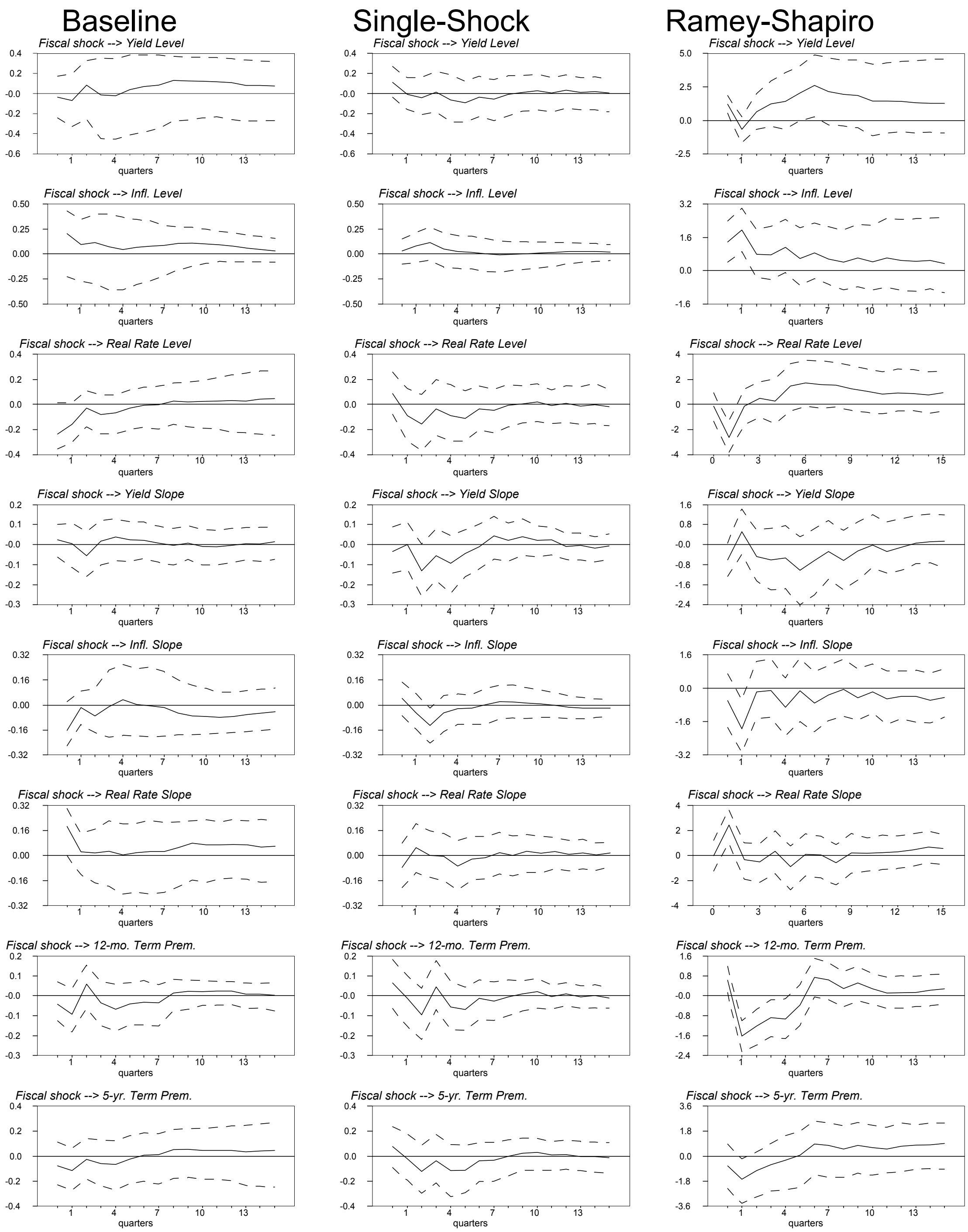

Figure 8: **Fiscal Shock Effects on the Yield Curve**

Impulse response functions following the baseline and single-shock fiscal impulses, and Ramey-Shapiro military build-ups. Dashed lines are Bayesian 90% probability error bands around the VAR point estimates.