

Economic Determinants of the Nominal Treasury Yield Curve

Charles L. Evans
Federal Reserve Bank of Chicago

David Marshall*
Federal Reserve Bank of Chicago

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Abstract

We study the effect of different types of macroeconomic impulses on the nominal yield curve. We employ two distinct approaches to identifying economic shocks in VARs. Our first approach uses a structural VAR due to Galí (1992). Our second strategy identifies fundamental impulses from alternative empirical measures of economic shocks proposed in the literature. We find that most of the long-run variability of interest rates of all maturities is driven by macroeconomic impulses. Shocks to preferences for current consumption consistently induce large, persistent, and statistically significant shifts in the level of the yield curve. In contrast, technology shocks induce weaker and less robust patterns of interest rate responses, since they move real rates and expected inflation in opposite directions. Monetary policy shocks are the only macroeconomic shocks with a consistent and significant impact on the slope of the yield curve. We find no evidence that fiscal policy shocks induce any significant interest rate responses.

*The paper represents the views of the authors and should not be interpreted as reflecting the views of the Federal Reserve Bank of Chicago or the Federal Reserve System.

1. Introduction

Vast amounts of information are rapidly assimilated into financial market prices. The Treasury yield curve is often cited as providing information on the current stance of monetary policy, the adequacy of fiscal revenue plans for delivering government services, 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).) To be more specific, nominal interest rate movements can be decomposed into real interest rate movements and changes in expected inflation. Changes in real interest rates should be associated with anything that changes the marginal product of capital, the intertemporal marginal rate of substitution for households, or changes in investors' risk tolerance. Inflation expectations should be related to expected monetary policy, which in turn is associated with macroeconomic aggregates through the central bank's policy rule (such as in a Taylor (1993) rule). For these reasons one would expect to find links between movements in the nominal Treasury yields and economic shocks.

While a major theme of finance research is to understand the factors that move the term structure, much recent work on this question assumes that interest rate changes are driven unobserved financial factors, rather than observable macroeconomic factors. (See Litterman and Scheinkman (1991), Knez, Litterman and Scheinkman (1994), and the empirical affine term structure literature described in Dai and Singleton (2000) and the references therein.) An important exception is Ang and Piassezi (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 one- and 12-month yields; these factors have a much smaller effect on long yields. Because the macro factors in their model affect primarily the shorter yields, these factors account for a good deal of the variation in the slope of the yield curve. However, they find little evidence that macroeconomic factors shift the level of the yield curve.

In this paper, we look at the effect of different types of macroeconomic impulses on the nominal yield curve. We use a variety of vector autoregression approaches that originated in the work of Sims (1980, 1986), Bernanke (1986), Blanchard and Watson (1986), among others. We start with an atheoretic empirical exercise that

simply asks whether the *slope*, *level*, and *curvature* of the yield curve is significantly affected by the block of macroeconomic variables. The only restriction we impose is to assume (following Ang and Piazzesi (2001)) that the three yields do not feed back to the macro variables. We confirm Ang and Piazzesi's (2001) result that a substantial portion of the variability of short- and medium-term yields is driven by macroeconomic factors. Unlike those authors, we find that most of the long-run variability of long-term rates is driven by macro impulses, and that the level of the yield curve responds strongly to macro factors. The strongest responses come from innovations that induce output and inflation responses in the same direction.

We then employ two distinct approaches to identifying economic shocks in VARs. Our first approach uses a structural VAR due to Galí (1992) that identifies fundamental macroeconomic impulses as aggregate supply shocks, a real aggregate demand (IS) shock, and a monetary policy shock. Our second identification strategy 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 alternative empirical measures of economic shocks that economists have proposed, often in the context of dynamic general equilibrium models. In assuming that we have noisy measures of the true economic shocks we seek to uncover, we can identify the linear combinations in the VAR innovations that yield these shocks. Our alternative measures are: Basu, Fernald, and Shapiro's (2001a,b) measure of technology shocks; Christiano, Eichenbaum, and Evans's (1996) measure of monetary policy shocks; Blanchard and Perotti's (2000) measure of fiscal policy shocks; and a measure of preference shocks examined by Hall (1997). We show how this information is easily incorporated into the standard analysis of VAR impulse response functions.

Our empirical analysis considers two decompositions of yield curve movements. First, we decompose movements in the level, slope, and curvature of the yield curve into those due to real interest rate movements and those due to inflation. Secondly, we decompose these movements according to changes in expected future short rates (the component that would follow the expectations hypothesis) and movements in term premiums.

We find evidence that macroeconomic factors have a substantial, persistent, and statistically significant effect on the level of the term structure. This finding stands in contrast to Ang and Piazzesi (2001), who find that the level of the yield curve is driven almost exclusively by latent variables orthogonal to their macro factors. The specific macro shocks that seem to move the level of the yield curve most strongly are those that move output and inflation in the same direction.

According to many empirical macroeconomists (e.g., see Blanchard (1989)), this sort of shock can be thought of as an aggregate demand shock. In the dynamic stochastic equilibrium literature, a shock to preferences for current consumption would have a similar effect. Empirically, under a variety of identification strategies, we find that an expansionary shock of this type moves expected inflation and real interest rates in the same direction, inducing a large response in the nominal rate. Furthermore, we find evidence that term premiums on long yields also rise, so the response of long yields is approximately the same as that of short yields. The effect of technology shocks (or aggregate supply shocks) is more muted. Technology shocks move real rates and expected inflation in opposite directions, attenuating the effect on the level of the yield curve. In most of our exercises, the response of expected inflation substantially exceeds the response of the real rate, so the yield level declines (although in only one case is this decline statistically significant). There is little evidence that technology shocks induce significant responses in term premiums. The only shock we find that has a significant and quantitatively important effect on the slope of the yield curve is the monetary policy shock. This response, however, is short-lived, dissipating in 6 months to one year. We find no evidence that interest rates have a quantitatively important response to fiscal policy shocks.

Our approach differs from that of Ang and Piazzesi (2001) in three important ways. First, we follow the literature on monetary policy shocks in allowing our indicator of monetary policy to feedback on macroeconomic variables in a flexible manner (as in Bernanke and Blinder (1992), Sims (1992), and Christiano, Eichenbaum, and Evans (1999)). Second, rather than simply looking at two macroeconomic indicators, we attempt to identify the fundamental economic shocks and to look at the way these shocks affect interest rates. Third, unlike Ang and Piazzesi (2001) 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 the basic statistical framework we use. 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). In section 4, we conduct our first exercise aimed at identifying the specific macroeconomic shocks that move interest rates. In that section, we use an identification

strategy that follows Galí (1992). Section 5 describes an alternative identification approach, in which we use measures of macroeconomic shocks derived from previous literature. We conduct three exercises using these shocks. Section 6 summarizes and discusses the results from all these exercises.

2. Basic statistical framework

We use the following vector autoregression (VAR) framework. 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 bond yield of different maturities. We estimate various restricted versions of the following structural VAR:

$$\begin{bmatrix} Z_t \\ R_t \end{bmatrix} = \begin{bmatrix} A(L) & \mathbf{0} \\ C(L) & D(L) \end{bmatrix} \begin{bmatrix} Z_{t-1} \\ R_{t-1} \end{bmatrix} + \begin{bmatrix} a & \mathbf{0} \\ c & d \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \gamma_t \end{bmatrix} \quad (2.1)$$

where a and d are nonsingular square matrices; c is a rectangular matrix, $\mathbf{0}$ is the zero matrix with appropriate dimensions; and $A(L)$, $C(L)$, and $D(L)$ are matrix polynomials in the lag operator L . The process $[\varepsilon_t, \gamma_t]'$ 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 (2.1) that identify the elements of ε_t as structural macroeconomic shocks. The elements of γ_t are yield shocks. The zero restrictions on the upper right-hand blocks of the coefficient matrices in (2.1) imply that neither the yields R_t nor the yield shocks γ_t enter the law of motion for the macroeconomic variables Z_t . This restriction is also made by Ang and Piazzesi (2001). The yield shocks γ_t are analogous to Ang and Piazzesi's (2001) vector of latent financial variables.

To estimate system (2.1), we estimate the following reduced form using ordinary least squares:

$$\begin{bmatrix} Z_t \\ R_t \end{bmatrix} = \begin{bmatrix} A(L) & \mathbf{0} \\ C(L) & D(L) \end{bmatrix} \begin{bmatrix} Z_{t-1} \\ R_{t-1} \end{bmatrix} + \begin{bmatrix} u_t \\ v_t \end{bmatrix} \quad (2.2)$$

where $[u_t \ v_t]'$ is the vector of OLS residuals. If the matrix a is known, then the structural shocks ε_t can be recovered from the OLS residuals via the relation

$$u_t = a\varepsilon_t \quad (2.3)$$

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

$$E[u_t u_t'] \equiv \Sigma_u = aa'$$

Therefore, an additional $n(n-1)/2$ *a priori* restrictions are needed to identify ε_t . Once ε_t is identified, one can compute variance decompositions and impulse responses in the usual way.

3. Initial empirical exploration

Our first exercise is simply an exploration of the data's properties. The data vector is given by $Z \equiv (Y, P, PCOM, FF)'$, where Y denotes the logarithm of industrial production, P denotes the logarithm of the personal consumption expenditure chain-weight price index, $PCOM$ denotes the smoothed change in an index of sensitive materials prices published by the Conference Board, 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, beginning in January 1959 through December 2000. The VAR incorporates 12 lags.

It is convenient expositionally to construct ε_t and γ_t in equation (2.1) by positing a lower-triangular structure for matrices a and d in system (2.1). 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 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 22% of the one-month-ahead conditional variance of the shortest yield is accounted for by macro variables (most of this is due to Federal Funds rate orthogonalized innovations), fully 86% of the 60-month ahead variance of this yield is attributable to macro factors. Most of this is due to the orthogonalized innovations other than the Federal Funds rate. Similarly, the fraction of the one-month ahead conditional variance for the 12- and 60-month yields explained by macro factors are only 17.5% and 10.8%, respectively. When we look at the 60-month ahead variance, these percentages rise to 84% and 86% for these two bonds. Again, for these longer yields most of the variance at the 60-month horizon is explained by the first three macro impulses, rather than the Federal Funds rate orthogonalized innovation.

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 Piazzesi and Ang (2001). However, our estimates of this statistic for the 60-month yield is much higher than that reported by Piazzesi and Ang (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. 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. We use a slightly different characterization. We follow Cochrane (2001) and take 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. The weights for this principal component decomposition are displayed in Table 2. Notice that the weights are close to those used by Ang and Piazzesi (2001). In particular, the level weights are approximately equal, the slope weights on the 1-month and 60-month yields are approximately the same magnitude but 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. Our measures of level, slope, and curvature have the advantage that they represent an orthogonal decomposition of the vector time series of yields. In practice, our measures of level, slope, and curvature display very similar behavior to the measures used by Ang and Piazzesi (2001).

In Figure 1, we plot the responses 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 upper and lower two-standard error bands, computed using 200 Monte Carlo simulations with bootstrapped residuals. 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 IP orthogonalized residual are 24, 22, and 16 basis points, respectively; the corresponding maximal responses of these yields to the PCOM residual are 29, 30,

and 24 basis points, respectively. Because the yields respond roughly in parallel, the yield level shifts upwards, but the yield slope and yield curvature responses are small and (mostly) insignificant.¹ The level responses are highly significant and very persistent.

The yield responses to the orthogonalized innovation to the price level are small and insignificant. The fed funds orthogonalized innovation moves the short yield substantially, with a progressively smaller response as the yield maturity lengthens. As a result, the primary effect of this shock is to shift the slope of the yield curve. Since the level is (approximately) an equally-weighted average of the three yields, the yield level also moves up, but by a smaller amount.

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 financial factors. In our system, macroeconomic factors have a much larger impact on the long yield. Our conjecture is that the key differences between the two approaches is that we allow for propagation of macro shocks through the monetary transmission mechanism.

To summarize, our first exercise indicates that a large fraction of the long-run variability of interest rates across all maturities is accounted for by macroeconomic impulses. There are combinations of macroeconomic innovations that have large, significant, and long-lived impacts on the level of the yield curve. The innovations with the largest nominal yield effects are associated with simultaneous increases in industrial production and inflation. However, unless substantially more structure is imposed on the VAR innovations, this description of the data's conditional second moment properties represents an incomplete characterization of the economic determinants of the nominal yield curve. In the following sections, we impose more economic structure to make inferences about these economic determinants.

4. Identification from a structural VAR

The principal economic driving processes in recently-studied dynamic general equilibrium models are technology shocks, monetary policy shocks, government spending and tax shocks, and shocks to preferences for current consumption services. Much of the structural VAR literature to date has focused each individual analysis on identifying a single shock. For example, Christiano, Eichenbaum and Evans

¹Throughout this paper, we refer to an impulse response as "significant" over a particular interval if the two-standard error bands exclude zero. bxtc

(1999) study monetary policy shocks, Galí (1999) studies technology shocks, and Ramey and Shapiro (1998) and Blanchard and Perotti (2000) study fiscal policy shocks. Galí (1992), however, is an important structural VAR paper that rigorously analyzes a large number of driving shocks.² Galí’s (1992) identification strategy imposes a mixture of long-run restrictions and contemporaneous impact restrictions to identify four economic shocks. Galí’s four shocks are a long-run aggregate supply shock (which we interpret as a technology shock); a transitory *IS* shock which affects aggregate demand; a monetary policy shock; and a residual shock that Galí interpreted as a money demand shock (but we interpret as a transitory supply shock). In this section, we study the implications of Galí’s identified economic shocks for the nominal yield curve. In section 5, we study model-based measures of these shocks to confirm the empirical findings here.

4.1. Galí’s identifying restrictions

We follow Galí in considering a four-variable autoregression for the macro system. The data vector is given by $Z \equiv (\Delta Y, FF, FF - \Delta P, \Delta M - \Delta P)'$, 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 real M1 balances. The data are monthly, beginning in January 1959 through December 2000. Identification is achieved with six restrictions on the covariance structure of the innovations. First, the monetary policy, transitory supply, and IS shocks have no long-run effect on output; these restrictions identify the long-run supply shock. Second, the monetary policy and transitory supply 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, and the remaining shock is determined.

4.2. Empirical results from Galí’s identification

Impulse responses implied by the Galí model, with two-standard error bootstrap bands, are displayed in Figure 2. The first 3 rows of the figure give responses

²Other important articles with many shocks include the original structural VAR contributions by Bernanke (1986), Blanchard and Watson (1986) and Sims (1986).

to the long run supply shock, the next 3 give responses to the aggregate demand (IS) shock, rows seven through nine give responses to the monetary policy (MP) shock, and the final 3 rows give the responses to the transitory supply shock. For each shock, we display responses of the macroeconomic variables (column one and the first graph in column three); the three yields (in column 2); and the level and slope of the term structure computed using weights in Table 2 as in section 3 (first graphs in columns 4 and 5). In addition, in the remaining graphs in columns 4 and 5, we plot the “inflation level”, “inflation slope”, “real rate level”, and the “real rate slope”. The former two weight the responses of one-month-, 12-month-, and 60-month-ahead inflation 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. The real rate level is the yield level minus the inflation level, and the real rate slope is the yield slope minus the inflation slope. These four plots thus decompose movements in the yield level and slope into the component due to the response of one-month, 12-month, and 60-month real rates and the component due to expected inflation.³ Finally, the last two graphs of column 3 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.⁴

Consider first the response of the macroeconomic variables to the four identified shocks. The directions of these responses can be reconciled with many implications from business cycle models. Following Blanchard (1989), an expansionary long-run supply shock induces opposite movements in output and the price level. It also induces a persistent rise in real interest rates, which is consistent with a shock that increases the marginal product of capital. The systematic response of monetary policy to the long-run supply shock reduces the federal funds rate. This response seems consistent with the implications of a simple Taylor (1993) rule: a positive aggregate supply shock expands productive capacity, so the increased output does not reflect an increase in the output gap while at the same time inflation falls. In contrast, a positive aggregate demand (IS) shock increases both

³To 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.

⁴These term premium responses are computed as the yield response for the 12- and 60-month yields, minus the cumulated response of the one-month yield over 12 and 60 months in the future, respectively. These cumulated one-month responses give the responses of the longer yields that would be seen if the expectations hypothesis held.

output and prices, so the systematic response of monetary policy is to tighten the funds rate. The responses following a monetary policy shock are similar to others found in the monetary policy response literature (see Christiano, Eichenbaum, Evans (1998) and Evans and Marshall (1998)): a monetary contraction reduces output and inflation while increasing the real rate.

Let us turn now to the response of nominal interest rates to these four shocks. The aggregate demand shock induces the largest yield responses, in terms both of the magnitudes of the responses and their statistical significance. The three yields increase between 15 and 25 basis points following a one-standard deviation positive aggregate demand shock, and these responses are long-lived, remaining significant over four years after the initial impulse. In contrast, the responses of yields to the long run aggregate supply shock are not statistically significant. While the point estimates are comparable to those induced by the aggregate demand shock, the responses are not statistically significant, since the zero line falls within the two-standard error bounds. The responses of yields to the monetary policy shock are similar to those found in Evans and Marshall (1998): A one-standard deviation contractionary monetary policy shock induces a positive but short-lived response in the shortest yields, with the magnitude of the response decreasing smoothly with maturity. The responses of interest rates to the fourth shock are small and insignificant.

Since the aggregate demand shock appears most important for interest rate movements, let us look more closely at the way this impulse affects the yield curve. The yields of all maturities respond similarly, so the aggregate demand shock raises the level of the yield curve without a significant change in the slope. The reason for this pronounced response of the yield curve level is that the aggregate demand shock shifts inflation and real rates in the same direction. The inflation level response is initially quite positive and significant, rising to 19 basis points at the third month following a positive impulse. As it decays thereafter, the real rate responds with a delay, peaking at 10 basis points in the fourth month and declining gradually. These two components reinforce each other, resulting in the significant yield level response. In contrast, the aggregate supply shock moves the real rate level and the inflation level in *opposite* directions. The only reason why the point estimates remain fairly large is that the inflation level response is quantitatively much more important than the real rate level response.

The response of the yield slope to both the aggregate demand and long run aggregate supply shocks, as well as the responses of the real rate and inflation components of the slope, are small and insignificant. The only shock that induces

a substantial change in the yield slope is the monetary policy shock, although this response is short-lived. While the effect of the monetary policy shock on the real-rate and inflation slopes are in opposite directions, the real-rate effect is so much stronger that it induces a shift in the slope of the nominal yield curve. In particular, short-term real rates increase by over 50 basis points, with much smaller effects on the two longer real rates. This induces a profound flattening in the real rate slope.

The small and insignificant slope response to the aggregate demand shock, and the persistence of the response of longer-term interest rates to this shock, are due in part to another factor: the significant and persistent response of term premiums. The expectations hypothesis, as characterized by Campbell and Shiller (1991), holds that term premiums are time-invariant. It is well-known that the expectations hypothesis fails to hold in post-war U.S. data. However, it is of interest to consider whether it holds *conditional* on a particular macroeconomic shock. That is, does the expectations hypothesis fail regardless of the shock that moves expected short rates, or is the failure of this hypothesis only in response to particular shocks? In rows 5 and 6 of column 3, we plot the response of the 12-month and 60-month term premiums to a positive aggregate demand shock. While these responses initially are insignificant, they become significant at about 5 basis points about 18 months after the impulse, remaining significant through the remaining 4-year horizon. While the magnitude of these term premium responses are small, they 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 aggregate demand shock, and much of the movement in the yield curve would be attributed to the slope, rather than the level. Note in Figure 2 that no other shock induces a significant response in the 12- and 60-month term premiums. In the context of the Galí model, one could conclude that the failure of the expectations hypothesis is due principally, and perhaps exclusively, to shocks to aggregate demand.⁵

⁵Another possibility is that the systematic response of monetary policy is different conditional on the realization of an aggregate demand shock compared with other shocks. If these policy actions inject a wedge into financial intermediation technologies, economy-wide risk-sharing could fall and risk premiums rise. We defer this to future research.

5. Identification from model-based shock measures

In the previous section, the Galí model placed strong *a priori* restrictions on the covariance structure of the VAR innovations to achieve identification. With a sufficient set of restrictions, identifying the economic shocks is always feasible if the space spanned by the VAR innovations is equivalent to the space spanned by the economic shocks. However, most lists of identifying restrictions in VARs are only roughly motivated by economic theory and are typically controversial. In this section, we introduce a different identification strategy with two novel features. First, the identifying restrictions are closely tied to specific economic theories. In particular, as in Prescott (1986) and Hall (1997), we exploit the ability of economic models to guide directly in the construction of noisy measures of the economic shocks. Second, few prior restrictions are placed on the covariance structure of the VAR innovations. As much as possible, we allow the model-based measures to dictate the VAR identification. To this end, we now describe our model-based measures of economic shocks and then provide three methods for computing impulse responses for the macroeconomic variables and interest rates.

5.1. Model-based measures of economic shocks

Our model-based measures of technology, preference, monetary and fiscal policy shocks relies heavily on research on fundamental shocks from antecedent articles. We derive shocks to preferences using an approach proposed by Hall (1997); we use a time-series for technology shocks estimated by Basu, Fernald, and Shapiro (2001a,b); we use a time series for fiscal policy shocks estimated by Blanchard and Perotti (2000); and we use shocks to monetary policy derived by Christiano, Eichenbaum, and Evans (1996).⁶ We will use the notation η_{mrs} , η_{tech} , η_{fiscal} and η_{mp} for the model-based shocks to preferences, technology, fiscal policy, and monetary policy, respectively.

⁶The alert reader will notice that since the Christiano, Eichenbaum, and Evans (1996) and Blanchard and Perotti (2001) shocks are derived from VARs, we are abusing somewhat the term “model-based shocks.” Nevertheless, we persist in using this terminology to maintain a clear distinction between the methods in this section versus previous structural VAR analyses.

5.1.1. Technology shocks

One-sector, dynamic general equilibrium models with full competition frequently specify a constant returns to scale technology

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

$$\ln z_t = \mu + \ln z_{t-1} + \varepsilon_{zt} \quad (5.1)$$

where Y , z , v , K , e , and N are the levels of output, technology, capital utilization rate, capital stock, labor effort, and labor hours. Standard Solow growth accounting implies that the technology innovation ε_{zt} can be measured as

$$\begin{aligned} \Delta \ln z_t &= \varepsilon_{zt} + \mu \\ &= \Delta \ln Y_t - \theta_t (\Delta \ln v_t + \Delta \ln K_t) - (1 - \theta_t) (\Delta \ln e_t + \Delta \ln N_t). \end{aligned}$$

There is a large empirical macroeconomic literature on measuring exogenous technological innovations that controls for endogenous features in measured Solow residuals. (For example, see Burnside, Eichenbaum and Rebelo (1993) and Braun and Evans (1998)). For our measure of the technology shock η_{tech} , we use a quarterly, aggregate measure of technology from Basu, Fernald, and Shapiro (2001a,b) which is based upon a constant returns to scale technology.⁷ Their measure controls for variable capital utilization rates, unobserved effort, and adjustment costs in investment. The data begin in 1965:II and end in 2000:IV. If specification (5.1) is correct and the variables are measured without error, then $\eta_{tech} = \varepsilon_z$. However, if the technology is misspecified, latent production factors are omitted, or the data measures do not match the theory, then η_{tech} will be a noisy measure of ε_z .

5.1.2. Preference shocks

Preference shocks have the potential to shift aggregate demand for goods and services. Hall (1997), Shapiro and Watson (1988) and Baxter and King (1991) find substantial business cycle effects from empirical measures of intratemporal marginal rates of substitution between consumption and labor (henceforth, “MRS shock”). The following approach generalizes Hall’s (1997) procedure to allow for time-nonseparable preferences. Consider a representative consumer with the following utility specification that includes external habit persistence

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

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

$$\ln \xi_t = \rho(L) \ln \xi_{t-1} + \varepsilon_{mrs,t} \quad (5.2)$$

where C is consumption of the representative agent, \bar{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)

$$\frac{\xi_t (C_t - b\bar{C}_{t-1})^{-\gamma}}{N_t^\phi} = 1/W_t$$

where W_t is the real wage. Taking logs yields

$$\ln \xi_t = \phi \ln N_t - \ln W_t + \gamma \ln [C_t - b\bar{C}_{t-1}].$$

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

This expression leads to an observable measure of ξ_t . 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. The utility function parameters are taken from previous studies. First, we set $\gamma = 1$. This corresponds to log utility for consumption services, which is a standard specification. 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 (2000).

We measure η_{mrs} as the residual in equation (5.2). We estimate a sixth-order polynomial for $\rho(L)$ and we allow for measurement errors in the consumption, real wage and labor hours data. In addition, the *MRS* measure ξ_t exhibits noticeable low frequency variation, so we also extract a linear time trend to account for demographic factors that are beyond the scope of this analysis. We estimate $\rho(L)$ and the trend term using instrumental variables.⁸ If there were no measurement errors and the estimated parameters were equal the true parameters, then $\eta_{mrs} =$

⁸Our 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.

ε_{mrs} . If the relationships above are misspecified or the data measures do not match the theoretical variables, then η_{mrs} will be a noisy measure of ε_{mrs} .

5.1.3. Monetary Policy Shocks

The empirical literature on monetary policy reaction functions suggests a number of identifications for monetary policy shocks (see Christiano, Eichenbaum, and Evans (1999)). In this study, we use as our η_{mp} measure an updated version of the monetary policy shock in Christiano, Eichenbaum, and Evans (1996). The variables in the VAR are the logarithm of real GDP, the logarithm of the GDP chain-weighted price index, the smoothed change in an index of sensitive materials prices published by the Conference Board, the Federal funds rate, the logarithm of nonborrowed reserves and the logarithm of total reserves. The data run from 1959:I through 2000:IV.

5.1.4. Fiscal Policy Shocks

The recent literature on fiscal policy shocks has offered a number of promising identifications (see Ramey and Shapiro (1998), Burnside, Eichenbaum and Fisher (1999), and Blanchard and Perotti (2000)). We use a time series for fiscal shocks derived by Blanchard and Perotti (2000)).⁹ These authors start with a three-variable VAR in GDP, government spending, and tax receipts. The latter two variables incorporate federal, state, and local measurements. Also, taxes are measured net of transfers, so the spending measure does not include transfers. Blanchard and Perotti then subtract off automatic responses of spending and taxes to shocks to GDP, and impose additional restrictions to identify exogenous shocks to taxes and government spending.¹⁰ We construct our overall fiscal shock η_{fiscal} as a shock to the government deficit, defined as the difference between the government spending shock and the tax shock. We use the shock measures that assume a deterministic trend. We have also performed the analysis with the individual tax and spending shocks. The results are qualitatively unchanged.

⁹We thank Roberto Perotti for providing us with his time series of fiscal policy shocks.

¹⁰Blanchard 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 model with deterministic time trends.

5.2. Responses to individual model-based shocks

Given a time series of a model-based shock, one method for computing impulse responses is simply to include the shock as another variable in the VAR and ordering its innovation first in a recursive scheme. Christiano, Eichenbaum and Evans (1999) use this approach to extract monetary policy shocks from Federal funds futures data. For each shock in our analysis, we compute an 8-variable VAR using the following quarterly variables: one of the 4 model-based shocks; four macroeconomic variables including GDP, the GDP price deflator, the commodity price index $PCOM$ measured at a quarterly frequency, and the federal funds rate. As before, we also include the one-, 12-, and 60-month zero coupon bond yields and we incorporate one year's worth of lags. The structure is analogous to equation (2.1), except that one of the four model-based shocks in turn is included as an 8th variable in the VAR. We orthogonalize the residuals using a recursive ordering, with the model-based shock ordered first. This is equivalent to treating the VAR residual for the shock equation as the structural impulse.

Before describing the results, two caveats should be mentioned. First, although the VAR literature typically assumes that the fundamental shocks have a diagonal variance-covariance structure, economic theories generally provide no deep explanation for the assumed correlation structure among model-based shocks. The correlation matrix of our model-based shocks is displayed in Table 3. Note that the correlations are fairly low, with the exception of $corr(\eta_{tech}, \eta_{fiscal})$, which exceeds 0.30. In considering each model-based shock individually in our analysis here, the effects of correlated shocks may be blurred together. In section 5.3 below, we describe two alternative procedures that can accommodate correlation among our noisy shock measures. Second, by introducing four additional variables into the macro VAR, we are assuming that there are four *additional* sources of exogenous macroeconomic variation. Our two alternative approaches below attempt to reduce the unknown sources of variation by identifying η_t directly with ε_t .

Turning to our empirical results in Figure 3, the design of this figure is analogous to Figure 2, except that, as described above, the responses to each individual shock are derived from different 8-variable VARs. Interestingly, the results are quite similar to those obtained from our Galí model in section 4. The two model-based shocks that would be most closely associated with the Galí *IS* aggregate demand shock would be the MRS shock and the fiscal policy shock. The MRS shock acts similarly to the aggregate demand shock in section 4, in that it induces a positive response in output, inflation, and the real interest rate (although the inflation response is insignificant). Of all four model-based shocks, the MRS shock

is the only one that induces a large, significant, and fairly long-lived response in all three yields. The responses of the one- and 12-month yields are similar, peaking at around 50 basis points in the third quarter following the shock. The response of the 60-month yield has a similar shape but is somewhat smaller in magnitude. These responses imply a significant and substantial shift upward in the level of the yield curve that lasts about two years. The main reason for this level shift is a pronounced increase in the real interest rate level. This is consistent with our interpretation of this shock as a transitory shock to the marginal utility of consumption. Furthermore, the large response of the yield level is due in no small part to a large and significant response of the term premiums. Notice that these term premium responses peak 3 quarters after the impulse. These peaks are mirrored in the responses of the yields themselves, and the term premium responses account for about one-half of the total response of these longer yields. Because the shorter rates initially increase more than the 5-year rate, the yield slope flattens significantly for the first two quarters. This flattening of the yield curve would last about two years were it not for the response of the term premiums, which offset the flattening of the yield curve by pushing longer rates up.

In contrast to this pronounced interest-rate response to the MRS shock, we find no significant responses of interest rates to either the technology shock or the fiscal policy shock. The point estimates of the yield responses to the fiscal policy shock are uniformly small and insignificantly different from zero. This is somewhat surprising given the results from the model of section 4, since one would normally think of fiscal policy as an important driver of aggregate demand. Taking these results at face value, one would conclude that the aggregate demand effects in section 4 are not primarily driven by exogenous fiscal policy shocks. However, the systematic response of monetary and fiscal policy to technology and preference shocks could still affect the term structure. Tracing out these systematic components is well beyond the scope of this paper.

Finally, the model-based monetary policy shock induces responses very similar to the monetary policy shock of section 4: a contractionary shock depresses output, reduces inflation (although insignificantly), increases real rates, induces a short-lived increase in the yield level and decrease (flattening) of the yield slope. Unlike the model of section 4, the model-based monetary policy shock does induce a statistically significant increase in term premiums about a year after the initial impulse.

5.3. Using model-based shocks to identify a structural VAR.

While the results above are suggestive, they are difficult to compare across shocks because the model-based shock measures are not orthogonal. Our alternative model-based shock identification assumes that the true economic shocks ε_t are linear combinations of the VAR residuals u_t , and that the model-based shocks η_t represent noisy measures of these true shocks. Specifically, rewrite equation (2.3) by defining $A \equiv a^{-1}$, so

$$A u_t = \varepsilon_t \quad (5.3)$$

with Σ_u and I being the $(n \times n)$ variance-covariance matrices of u_t and ε_t , respectively. We assume that the $(n \times 1)$ vector of model-based shocks η_t is related to the economic shocks ε_t by

$$\eta_t = D \varepsilon_t + w_t \quad (5.4)$$

where D is a non-singular $(n \times n)$ matrix and w_t is a vector of measurement errors independent of ε_t .

Identification comes down to uniquely determining the matrices A and D given the population moments from the VAR innovations u_t and noisy measures η_t . First, note that the covariance matrix $\Sigma_{u\eta} \equiv E[u_t \eta_t'] = E[A^{-1} \varepsilon_t (\varepsilon_t' D' + w_t')] = A^{-1} D'$. This can be restated simply as

$$A = D' \Sigma_{u\eta}^{-1}. \quad (5.5)$$

This condition is important: since $\Sigma_{u\eta}$ can readily be computed from the data, A could be identified with no a priori restrictions if D were known. In effect, this shifts identifying restrictions from matrix A to matrix D . 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.

To estimate D , the standard VAR identification condition,

$$A \Sigma_u A' = I \quad (5.6)$$

can now be restated as

$$D' \Sigma_{u\eta}^{-1} \Sigma_u \Sigma_{u\eta}^{-1} D = I \quad (5.7)$$

As in the typical identified VAR, $n(n-1)/2$ a priori identifying restrictions on D are required. Some η measures may be linear combinations of the underlying shocks, perhaps due to mismeasurement in the way the series in η were

computed.¹¹ Alternatively, in the situation where each element of η is a direct measure of ε , then D would be diagonal and the system would be overidentified. Whenever the system is overidentified, equation (5.7) will not hold exactly in finite samples. Nevertheless, one can still compute D by using the maximum likelihood procedure described in Hamilton (1994, pp.331-332). Matrix A can then be computed using equation (5.5) However, the resulting A matrix will not factor Σ_u since equation (5.7) does not hold exactly. We refer to this case as the *overidentified system*.

In the case where exactly $n(n - 1)/2$ restrictions on D are imposed, the system is exactly identified, and a unique A matrix exists satisfying equations (5.6) and (5.7). We restrict our attention to exactly identified systems where D is lower triangular. In this case, the A matrix can be computed directly as follows. Substitute equation (5.3) into equation (5.4) to get

$$\eta_t = Cu_t + w_t \tag{5.8}$$

where

$$C \equiv DA. \tag{5.9}$$

Since w_t is uncorrelated with ε_t , it is also uncorrelated with u_t , so the matrix C can be estimated from equation (5.8) by ordinary least squares. Given our estimates of C and Σ_u , equations (5.6) and (5.9) imply that

$$DD' = C\Sigma_uC'.$$

We can then compute D as the unique lower triangular factorization of $C\Sigma_uC'$. Matrix A is then computed as $A = D^{-1}C$.

As equation (5.8) shows, the model-based shocks 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^2 s for the *OLS* regressions in system (5.8) using the measures of $\eta_t = (\eta_{mp}, \eta_{mrs}, \eta_{tech}, \eta_{fiscal})'$ described in section 5.1. As in section 5.2, we use four macroeconomic variables in the VAR: GDP, the GDP price deflator, the commodity price index *PCOM*, and the federal funds rate. The only model-based shock that looks problematic from this perspective is the fiscal shock, whose R^2

¹¹For example, if standard measures of Solow residuals are not purged of labor hoarding components, then they will be contaminated with other shock measures as well. Evans (1992) found evidence of such contamination in Prescott's (1986) measure.

is only 8.7%.¹² This suggests that our fiscal shock measure η_{fisc} may not provide strong identification for an underlying fiscal shock in the context of our VAR system. As a result, we exercise caution in interpreting the responses to the fiscal shock implied by this exercise.

5.4. Empirical results using model-based shocks in an over-identified system

The most straightforward assumption linking the model-based shocks to the true underlying shocks is to assume that each element of η_t equals the corresponding element of ε_t plus measurement error. In this case, D is diagonal, the system is overidentified, and $A^{-1}A'^{-1} \neq \Sigma_u$ in finite samples. In practice, this latter fact leads to the counterfactual implication that more than 100 percent of the variation in output and other variables is accounted for by the economic shocks. In the overidentified analysis here, we attempt to mitigate this by multiplying A by a scalar in order to match the variance of output innovations. Due to the nonlinear maximization in estimating D , it is impractical to compute standard error bands solely from bootstrap methods (see Sims and Zha (1999) for a related discussion). In addition, the uncertainty induced by estimating (5.4) complicates the error band calculations in ways beyond standard structural VAR analyses. We defer a complete derivation and discussion of alternative error band calculations for further research, as it is beyond the scope of this paper. Instead, we report approximate two-standard error bands in Figure 4 that are computed using a mixture of bootstrap and Bayesian Monte Carlo methods, the latter following Sims and Zha (1999).¹³

¹²Our measure of η_{fiscal} is the difference between the government spending shock and the tax shock, both estimated by Blanchard and Perotti (2001). When we estimate regression (5.8) using the spending shock or the tax shock individually, the R^2 s are all below 6%.

¹³We use the following strategy to compute approximate standard errors for our overidentified system. For each simulation j , the VAR coefficients and innovations are constructed using standard bootstrap methods. Given a vector time series of innovations $u_t^{(j)}$ for simulation j , we constructed $\eta_t^{(j)} = Cu_t^{(j)} + w_t^{(j)}$ where the measurement errors $w_t^{(j)}$ were drawn at random with replacement from the actual time series of errors. The time series on $\eta_t^{(j)}$ and $u_t^{(j)}$ are used to compute $\Sigma_{u\eta, (j)}^{-1}$. Following Sims and Zha (1999), we draw $D^{(j)}$ from a second-order Taylor expansion of the posterior distribution for D (conditional on $\Sigma_{u\eta}^{-1}$ as well as Σ_u). This leads to a Monte Carlo draw for $A^{(j)} = D^{(j)'\Sigma_{u\eta, (j)}^{-1}}$, and this is multiplied by a scalar in order to match the variance of the simulated output innovations for draw j . The scaled $A^{(j)}$ is used to compute the impulse responses for draw j . As a final note, we employed no weighting scheme in drawing

The results in Figure 4 are similar to the model-based one-at-a-time results in Figure 3. The MRS shock continues to behave like the Galí *IS* shock, inducing positive responses in output, inflation, real interest rates and the federal funds rate. Again, the inflation response is not significant. The MRS shock induces the largest, most significant, and most persistent response in all three yields. The nominal yield level rises significantly, due primarily to a significant increase in the level of real interest rates. However, the term premium responses are not significant.

For technology there is a significantly positive response of the nominal yield level after 3 quarters, due to an increase in real interest rate levels. This is in contrast to the results for the technology shock taken alone, where the yield response was insignificant. For monetary policy, the results are quite similar to the results in section 5.2, when the model-based shock was viewed in isolation. Finally, the fiscal shock again produces no significant effects on anything. This result may suggest either that fiscal shocks have little impact on macroeconomic or financial variables. Alternatively, this measure of fiscal shocks may be ill-suited for the exercises conducted in this paper.

5.5. Empirical results using model-based shocks in an exactly-identified system

In order to get an unambiguous decomposition of variance, we estimate an exactly-identified version of equation (5.7). We do so by assuming that D is lower triangular. In particular, we focus on the following extension of system (5.4) that incorporates lower triangularity:

$$\begin{bmatrix} \eta_{mp} \\ \eta_{mrs} \\ \eta_{tech} \\ \eta_{fiscal} \end{bmatrix} = \begin{bmatrix} d_{11} & 0 & 0 & 0 \\ d_{21} & d_{22} & 0 & 0 \\ d_{31} & d_{32} & d_{33} & 0 \\ d_{41} & d_{42} & d_{43} & d_{44} \end{bmatrix} \begin{bmatrix} \tilde{\varepsilon}_{mp} \\ \tilde{\varepsilon}_{mrs} \\ \tilde{\varepsilon}_{tech} \\ \tilde{\varepsilon}_{fiscal} \end{bmatrix} + w \quad (5.10)$$

where we use the notation $\tilde{\varepsilon}_{mrs}$, $\tilde{\varepsilon}_{tech}$, $\tilde{\varepsilon}_{fiscal}$ and $\tilde{\varepsilon}_{mp}$ for the true underlying shocks to preferences, technology, fiscal policy, and monetary policy, respectively. We adopt this ordering for the following reasons. First, monetary policy shocks have been the most studied VAR shock in the literature. Evans and Marshall (1998) study

the approximate posterior distribution for D . This method is asymptotically justified, but computing error bands with more efficient small-sample properties continues to be an area of active research.

how monetary policy shocks identified using different methodologies (including that described in section 5.1.3 for our η_{mp} measure) affect interest rates. The implications are robust across the different identifications, suggesting that η_{mp} is a fairly robust measure of this policy shock. In addition, η_{mp} has already been regressed on several contemporaneous measures of real activity and prices, so it is less likely to be contaminated with other shocks that move these variables. For these reasons, η_{mp} is likely to be the cleanest measure in our η_t vector. Second, Table 4 shows that the fiscal policy shock measure has the smallest correlation with the VAR innovations u_t of all of our η_t elements. Consequently, this row of the matrix C is likely to be estimated imprecisely, so we wish to limit the influence of the fiscal policy measures on the other analyses. Furthermore, Blanchard and Perotti's (2000) VAR analysis consists of a small three-variable VAR: it can be argued that this shock is contaminated by innovations from omitted variables that would be included in larger systems. These considerations motivate us to place the fiscal policy measure last in the ordering. Finally, there is no obvious reason for ordering the MRS shock ahead of the technology shock, so we will discuss the robustness of our results when we switch the order of η_{mrs} and η_{tech} .

The results for ordering (5.10) are in Figure 5. The responses to the policy shocks $\tilde{\epsilon}_{mp}$ and $\tilde{\epsilon}_{fiscal}$ are very similar to those found in section 5.2 for the raw shocks η_{mp} and η_{fiscal} . In particular, a contractionary shock to monetary policy induces a significant decrease in output, a decrease in inflation that is largely insignificant, an increase in the real rate, a significant but short-lived increase in the yield level and a marked flattening of the yield slope. This response of the yield slope to $\tilde{\epsilon}_{mp}$ is somewhat stronger than the response to η_{mp} found in section 5.2, lasting approximately one year. There are no significant term premium responses to $\tilde{\epsilon}_{mp}$. The responses to $\tilde{\epsilon}_{fiscal}$ under identification (5.10) are all insignificant. While our placing the fiscal shock fourth in the ordering in (5.10) would tend to render its effects less pronounced, we found similar insignificance in the responses to the raw fiscal shock η_{fiscal} , reported in section 5.2.

The responses to preference shock $\tilde{\epsilon}_{mrs}$ differ somewhat from those to the raw shock η_{mrs} . The responses of real GDP and inflation to $\tilde{\epsilon}_{mrs}$ appear much more persistent than the corresponding responses to η_{mrs} . The inflation response is larger and positive throughout. (The inflation response to η_{mrs} , described in section 5.2, fluctuated closely around zero.) This inflation response corresponds more closely to that of the aggregate demand shock discussed in section 4. The federal funds and real rate responses look similar to those in section 5.2. The response of the yield level is more pronounced in system (5.10) than in the exper-

iments of section 5.2 because the inflation level is bigger and positive throughout. Finally, the responses of the term premiums in this identification are large and significant.

The identifying restrictions in (5.10) purge the technology shock of any lingering effects of the preference shock. While Table 3 shows that the unconditional correlation between technology and preference shocks is small (around 5%), it appears that the ordering used in (5.10) has a substantial effect on the response of output and inflation to the technology shock. First, output does not respond initially to the technology impulse, but begins to rise after one year. This is consistent with the empirical and theoretical analyses of Galí (1999), Basu, Fernald, and Kimball (2000), and Francis and Ramey (2000). Galí (1999) and Basu, Fernald and Kimball (2000) interpret this delay as evidence of inertial aggregate demand due to price stickiness, while Francis and Ramey interpret the delay as consistent with inertial aggregate demand due to habit persistence in consumption and investment adjustment costs. Interestingly, when we reverse the order of η_{mrs} and η_{tech} in equation (5.10) (as in section 5.6, below) we no longer get this delayed output response. This suggests that the raw technology shock η_{tech} may be contaminated with the effect of the MRS shock. This contamination is eliminated when the ordering in system (5.10) is used.

Second, one would expect that a positive technology shock should have a substantial negative effect on inflation. For example, in a model with monopolistic competition, where prices are set as a mark-up over marginal cost, a technology shock that reduced marginal costs would be deflationary. In sections 5.2 and 5.4, inflation does respond negatively to the technology shock, but the response is weak and short-lived. In contrast, the response of inflation to $\tilde{\epsilon}_{tech}$ under the lower-triangular identification (5.10) is quite large (around 40 basis point in response to a one-standard deviation $\tilde{\epsilon}_{tech}$ shock) and persists significantly for about two years. The real-rate response is smaller and shorter-lived, as in sections 5.2 and 5.4. The large size and persistence of the deflationary response, relative to the real rate response, induces a large, significant, and persistent *decrease* in the yields of all three maturities. Note that the maximal responses of the three yields are decreases of between 38 and 46 basis points. In addition, this measure of the technology shock induces large and significant declines in the term premiums after three years. As a result of these effects, the yield level drops substantially, significantly, and with great persistence. This identification strategy is the only one that implies an important level response for the yield curve in response to a technology or aggregate supply shock. The responses of the yield slope and of

the term premiums are insignificant.

5.6. Permuting the order of the preference and technology shocks

In system (5.10), we placed η_{mrs} second and η_{tech} third in the recursive ordering. This is equivalent to assuming that $\tilde{\varepsilon}_{mrs}$ may affect η_{tech} but $\tilde{\varepsilon}_{tech}$ does not affect η_{mrs} . We have performed the analysis with this ordering reversed. The qualitative responses to the MRS shock are the same as in system (5.10). An impulse to $\tilde{\varepsilon}_{mrs}$ significantly increases both output and inflation, induces a significant upward shift in the level of the yield curve and in the 12- and 60-month term premiums. However, the quantitative magnitudes of these effects differ from those in system (5.10). In particular, the output effect is smaller and less persistent, but the inflation effect is considerably larger.

In contrast, the effect of $\tilde{\varepsilon}_{tech}$ on interest rates becomes much less pronounced when the ordering is reversed. The reason is that while the response of output to $\tilde{\varepsilon}_{tech}$ is considerably larger, the response of inflation is almost zero. Since the significant response of nominal yields to $\tilde{\varepsilon}_{tech}$ in the (5.10) ordering is primarily due to the large and significant response of expected inflation, this attenuation of the inflation response when the ordering is reversed effectively eliminates any significant interest rate response. A possible explanation for this result is that our model-based technology shock η_{tech} may be contaminated with the effects of $\tilde{\varepsilon}_{mrs}$. If so, this would tend to reduce the inflation response, since an expansionary preference shock tends to move inflation in a direction opposite to that of an expansionary technology shock. In that case, ordering (5.10) would be preferable. More generally, if one has a strong prior belief that technology shocks ought to elicit a response in the inflation rate, this result would constitute evidence against the $(\eta_{tech}, \eta_{mrs})$ ordering and in favor of the $(\eta_{mrs}, \eta_{tech})$ ordering (5.10).

6. Summary, discussion, and conclusion

When we look across the various empirical models used in this paper, several results stand out. First, a shock that increases household's preference for current consumption, as opposed to current leisure or future consumption, seems to have the biggest effect on interest rates across all maturities. This shock seems to be associated with the aggregate demand shock in the Galí model, in that both the preference shock and the aggregate demand shock move output and inflation in the same direction. Regardless of identification strategy, this sort of shock induces

a large, persistent, and statistically significant shift in the level of the yield curve.

There are two ways of further analyzing this result. First, from a Fisherian perspective, the nominal yield is the sum of the real yield and expected inflation over the life of the bond. The preference/aggregate demand shock has a large effect on nominal interest rates because it moves real rates and expected inflation in the same direction. The two effects reinforce each other. These patterns are not difficult to reconcile with economic theory. An exogenous increase in household preference for current consumption would cause households to want to borrow from the future. Real interest rates must rise in order to enforce the constraint that there be zero net borrowing in equilibrium. At the same time, an increase in the relative utility of goods vs. leisure would tend to increase the equilibrium quantity of labor supplied, raising the marginal product of capital. This, too, would tend to raise the real rate. At the same time, an increased demand for goods would increase firms' marginal costs. In a model of monopolistic competition where prices are set as a markup over marginal cost, this would increase inflation (unless there is a compensating contraction in monetary policy).

A second way of analyzing this result is from the perspective of the expectations hypothesis. The preference/aggregate demand shock is the only one to consistently induce a significant response in term premiums, defined as the difference between actual long yields and the yield predicted by the pure expectations hypothesis. (Significant term premium responses were also found for the technology shock in the identification system of section 5.5 and the monetary policy shock in section 5.2.) We find that when the preference/aggregate demand-type shock increases the short-term interest rate, it increases long-term interest rates by about the same amount because it induces a rise in the term premiums. Since term structure theory associates variation in term premiums with variation in the market price of risk, this result suggests a deeper question: why would the price of risk respond only to this particular macroeconomic impulse? In asset-pricing models such as Campbell and Cochrane (1999) and Wachter (2001), the main reason for time-variation in the price of risk is business-cycle fluctuation. In principle, business cycles are driven by the entire vector of macroeconomic shocks. Our result suggests that the price of risk responds differently depending on the source of the business cycle impulse. In particular, a preference-driven recession (e.g., in the language of the press, an exogenous decline in "consumer confidence") would induce a bigger increase in household risk aversion than a technology-driven recession. Why this should be is not at all clear, but it suggests a direction for future research.

A second result from our work concerns the type of macroeconomic shock that moves output and inflation in opposite directions. Technology shocks and aggregate supply shocks have this property. These sorts of shocks move real interest rates and expected inflation in opposite directions, attenuating their impact on nominal yields. The response of nominal interest rates to these shocks tends to be weaker, and less significant than the responses to the preference/aggregate demand shocks. The direction of the interest rate response to technology/aggregate supply shocks depends on whether the real rate response or the expected inflation response dominates. We did not obtain robust results on this question. Thus, whether this type of shock has a significant impact on the yield curve is still an open question, depending sensitively on the identification strategy used.

Finally, the only shock that consistently shifts the slope of the yield curve is the monetary policy shock. A contractionary shock induces a large, significant, but short-lived increase in the short-term real interest rate, with a much smaller effect on longer term real rates. This reduces the slope of the real yield curve. At the same time, in three of our four exercises sections 5.2, 5.4, and 5.5), the contractionary shock reduces the inflation slope. This is because the inflationary response to the monetary contraction is sluggish, so the initial impact on long-term expected inflation actually exceeds the impact on short-term inflation. The combination of these two effects induces a significant reduction in the slope of the nominal yield curve. However, the effect dissipates in 6 months to one year.

Our results suggest specific macroeconomic impulses that may account for the slope and level effects identified as key drivers of the yield curve in empirical finance research such as Litterman and Scheinkman (1991), Knez, Litterman and Scheinkman (1994), and Dai and Singleton (2000). In addition, they represent a set of empirical patterns that dynamic equilibrium models ought to accommodate. Finally, they motivate future research to help us understand how systematic monetary policy interacts with fundamental shocks to induce movement in the nominal yield curve.

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Table 1: Decomposition of Variance under Recursive Orthogonalization

Panel A: Decomposition of Variance of One-Month Yield

Steps ahead:	1-month	12-months	60-months
ε_Y	0.014 (-0.01,0.042)	0.176 (0.042,0.311)	0.230 (0.011,0.448)
ε_{PCOM}	0.022 (-0.01,0.057)	0.329 (0.182,0.476)	0.488 (0.268,0.708)
ε_P	0.022 (-0.01,0.057)	0.008 (-0.02,0.039)	0.035 (-0.07,0.140)
ε_{FF}	0.168 (0.088,0.249)	0.209 (0.095,0.323)	0.106 (-0.00,0.214)
γ_1	0.779 (0.702,0.856)	0.278 (0.192,0.364)	0.141 (0.052,0.231)

Panel B: Decomposition of Variance of 12-Month Yield

Steps ahead:	1-month	12-months	60-months
ε_Y	0.048 (0.006,0.090)	0.192 (0.047,0.337)	0.243 (0.005,0.481)
ε_{PCOM}	0.031 (-0.00,0.069)	0.328 (0.168,0.488)	0.526 (0.280,0.771)
ε_P	0.004 (-0.01,0.020)	0.008 (-0.02,0.042)	0.032 (-0.04,0.114)
ε_{FF}	0.092 (0.033,0.151)	0.054 (-0.01,0.122)	0.032 (-0.04,0.114)
γ_1	0.176 (0.074,0.277)	0.089 (0.027,0.151)	0.035 (-0.00,0.077)
γ_2	0.649 (0.529,0.769)	0.329 (0.216,0.443)	0.129 (0.025,0.234)

Panel C: Decomposition of Variance of 60-Month Yield

Steps ahead:	1-month	12-months	60-months
ε_Y	0.039 (0.00,0.081)	0.160 (0.023,0.298)	0.188 (-0.05,0.429)
ε_{PCOM}	0.040 (0.004,0.075)	0.305 (0.149,0.460)	0.584 (0.327,0.841)
ε_P	0.002 (-0.00,0.013)	0.016 (0.00,0.057)	0.068 (0.00,0.214)
ε_{FF}	0.027 (0.00,0.064)	0.010 (0.00,0.047)	0.019 (0.00,0.101)
γ_1	0.069 (0.012,0.126)	0.039 (0.003,0.076)	0.011 (0.00,0.027)
γ_2	0.518 (0.437,0.600)	0.296 (0.201,0.392)	0.082 (0.000,0.164)
γ_3	0.305 (0.252,0.357)	0.174 (0.121,0.227)	0.048 (0.000,0.096)

Legend: $\varepsilon_Y, \varepsilon_{PCOM}, \varepsilon_P,$ and ε_{FF} denote the orthogonalized residuals to industrial production, commodity price index, the price level, and the federal funds

rate. γ_j denotes the orthogonalized residual to the j -month yield. In the decomposition used here, matrix d in equation (2.1) is lower triangular, so γ_2 and γ_3 do not affect the one-month yield, and γ_3 does not affect the 12-month yield. Numbers in parentheses are upper and lower two-standard deviation bounds, computed using 200 Monte Carlo draws with bootstrapped residuals.

Figure 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

Legend: 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

Legend: 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%

Figure 1: Recursive Orthogonalization

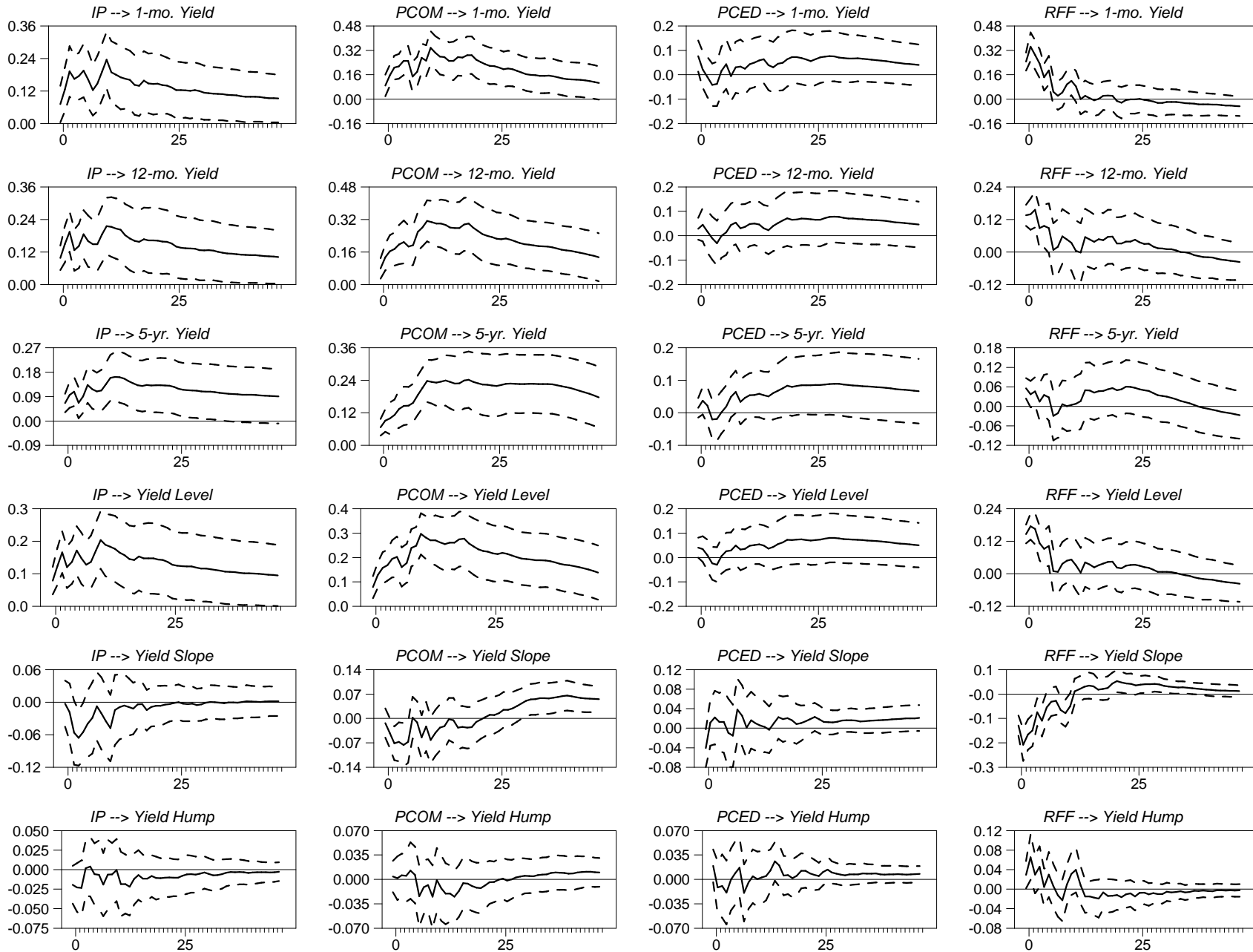


Figure 2: Gali Model

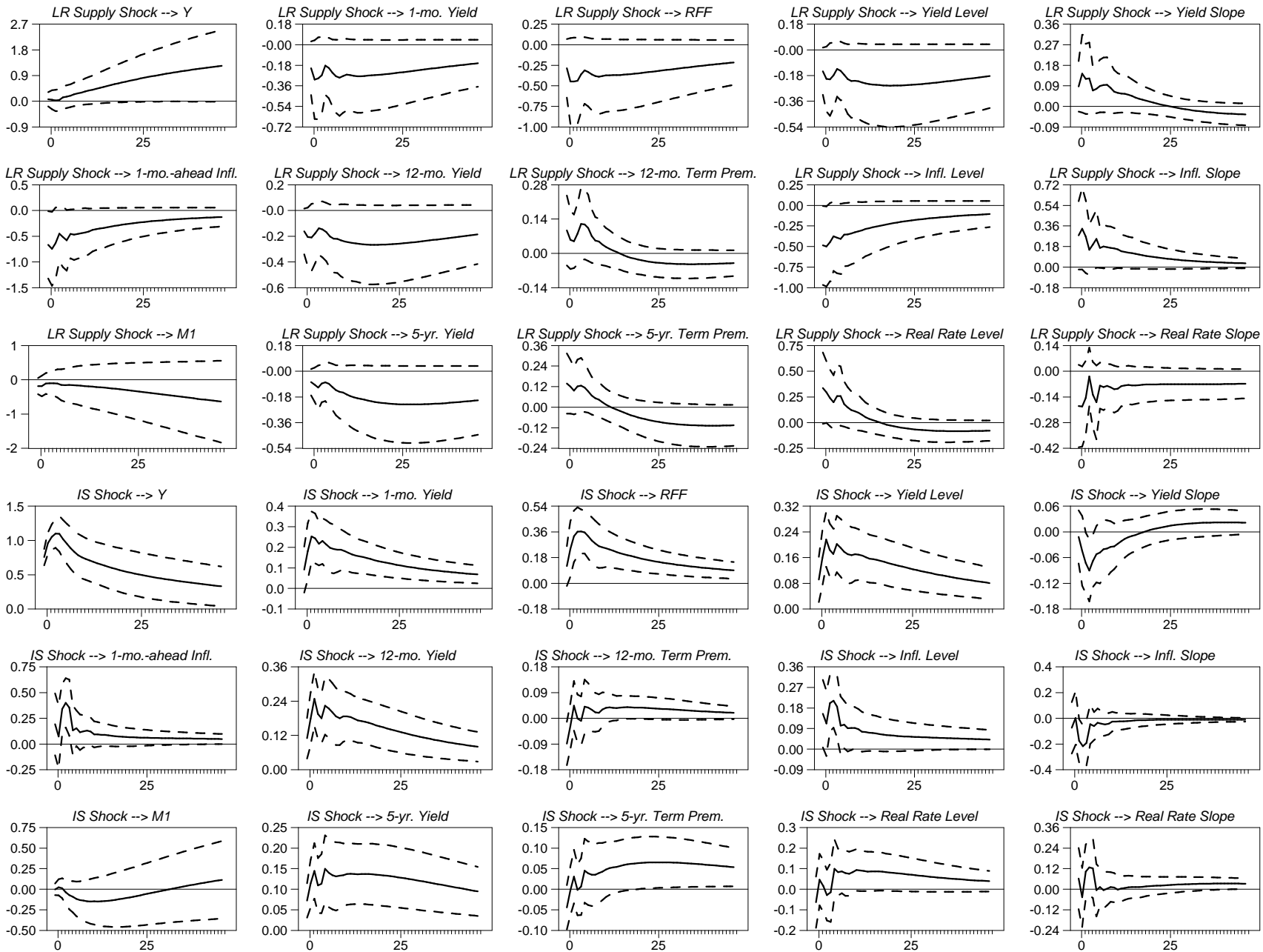


Figure 2 (continued)

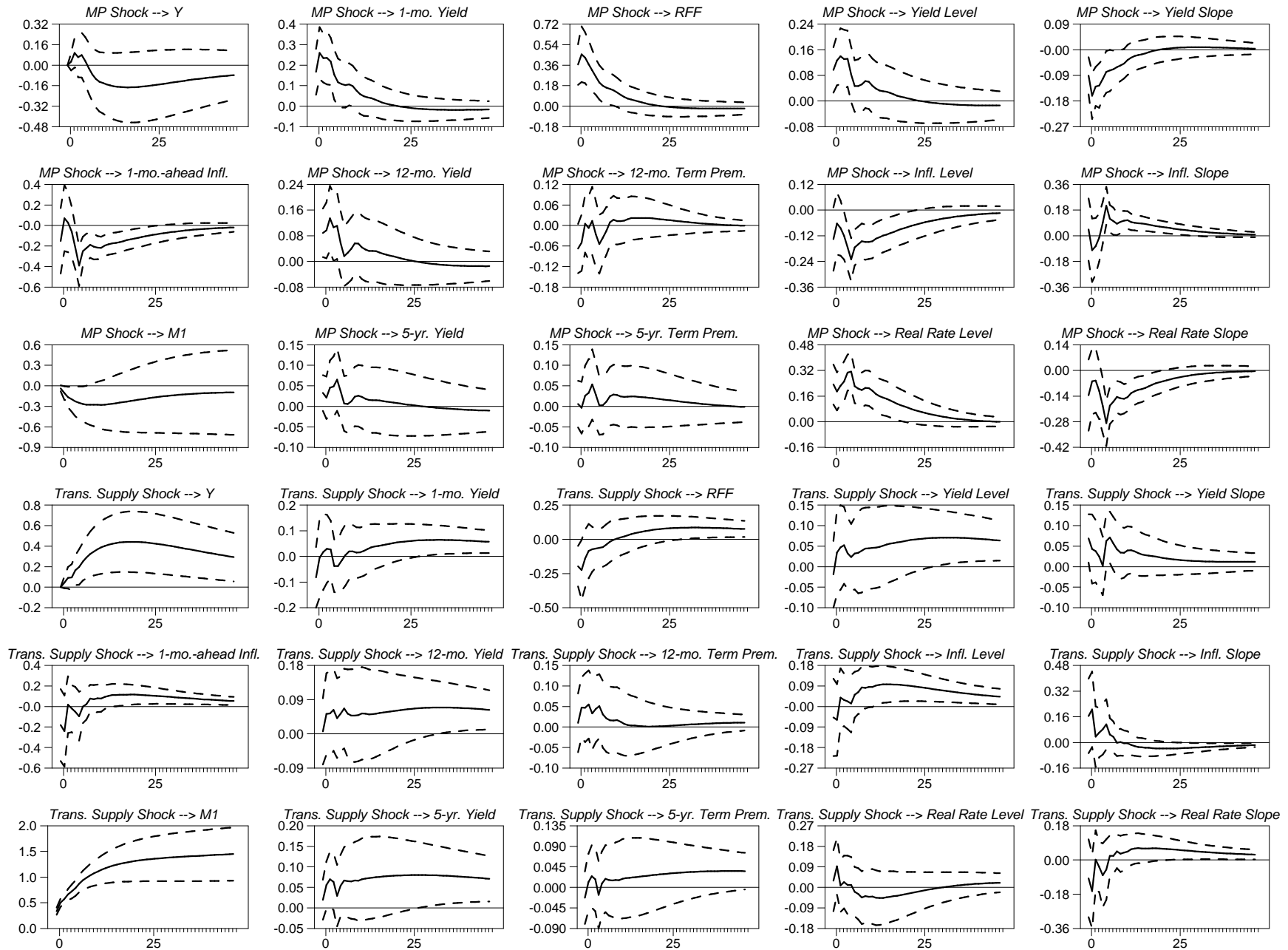


Figure 3: Responses to Individual Model-Based Shocks

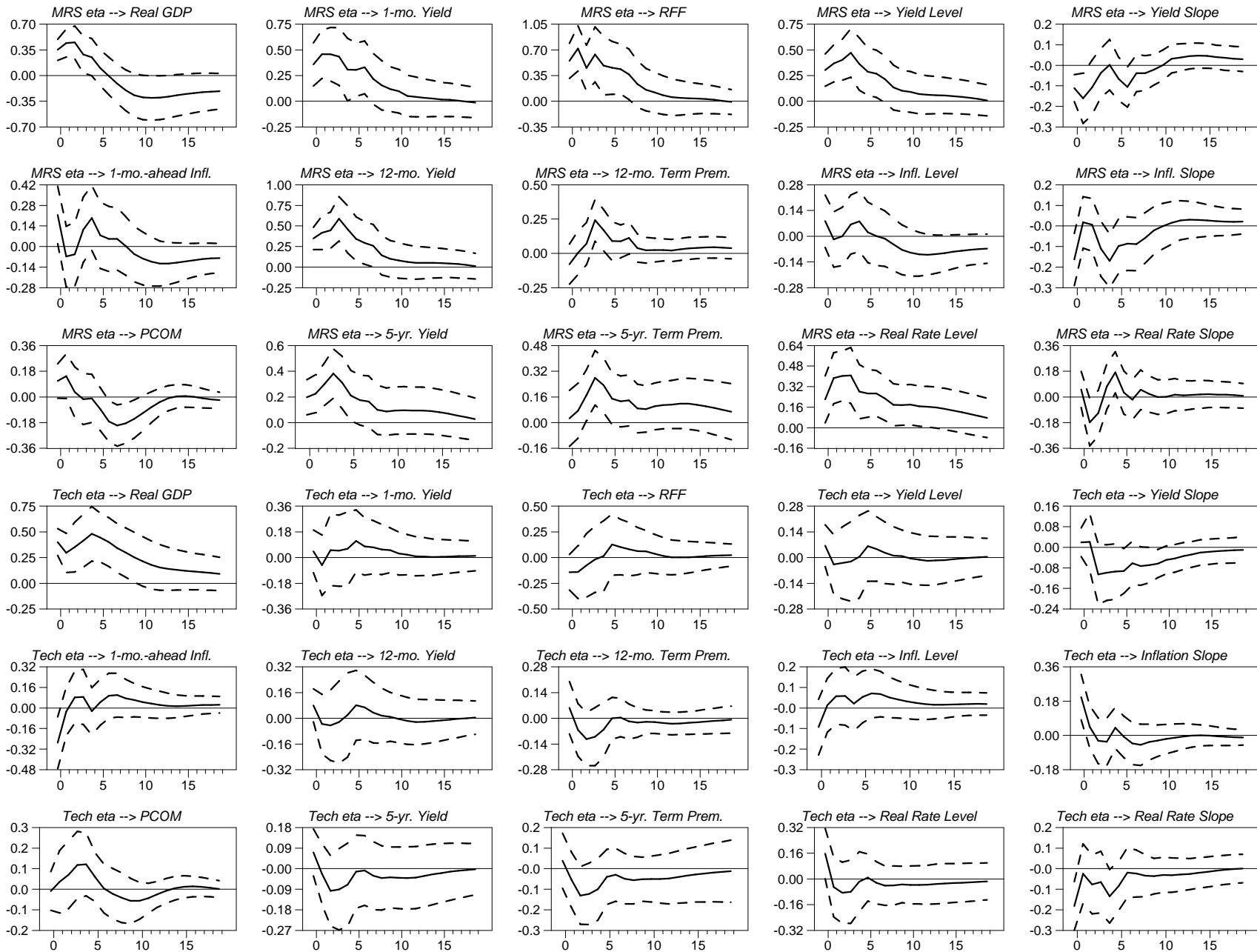


Figure 3 (continued)

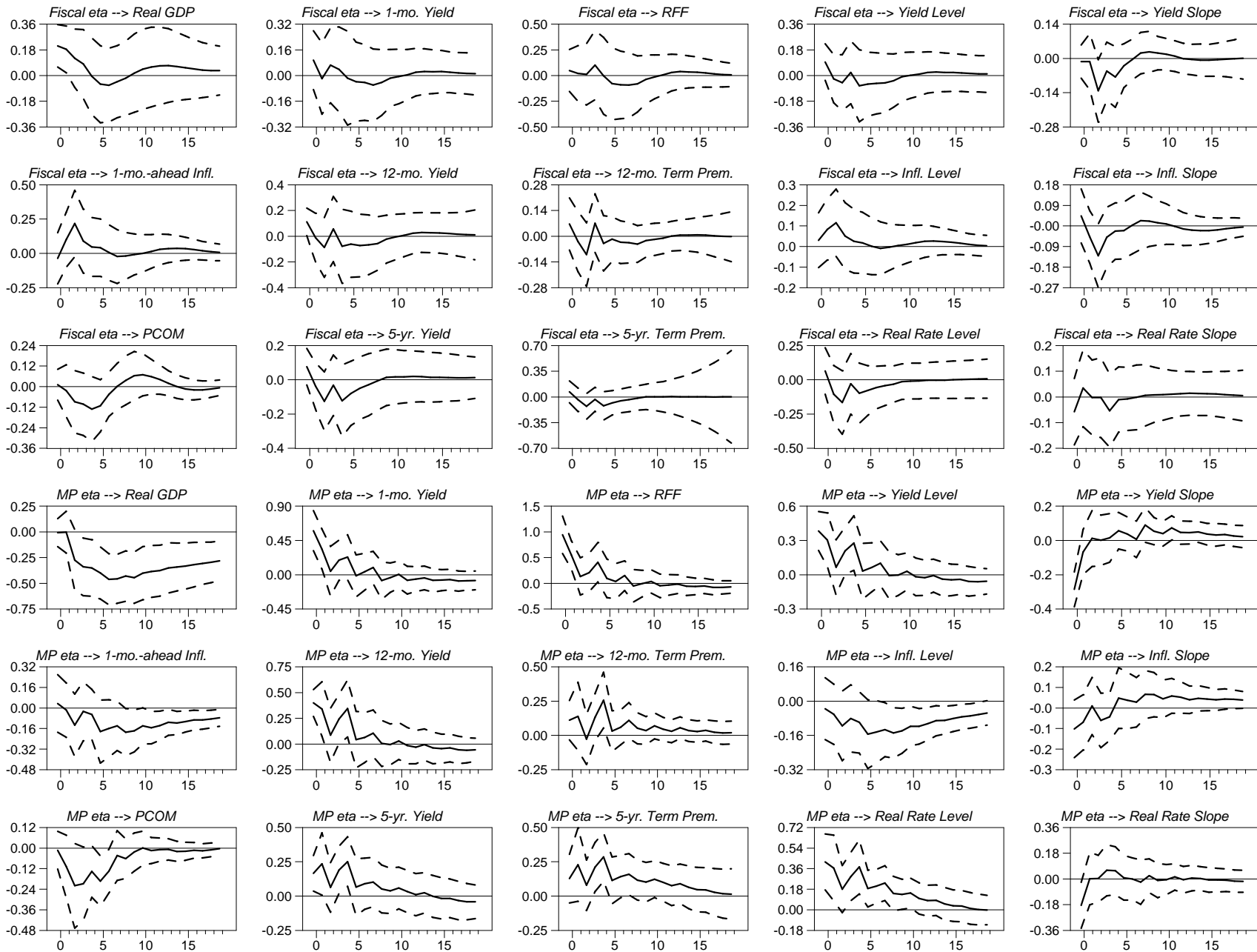


Figure 4: Over-Identified VAR: Diagonal D Matrix

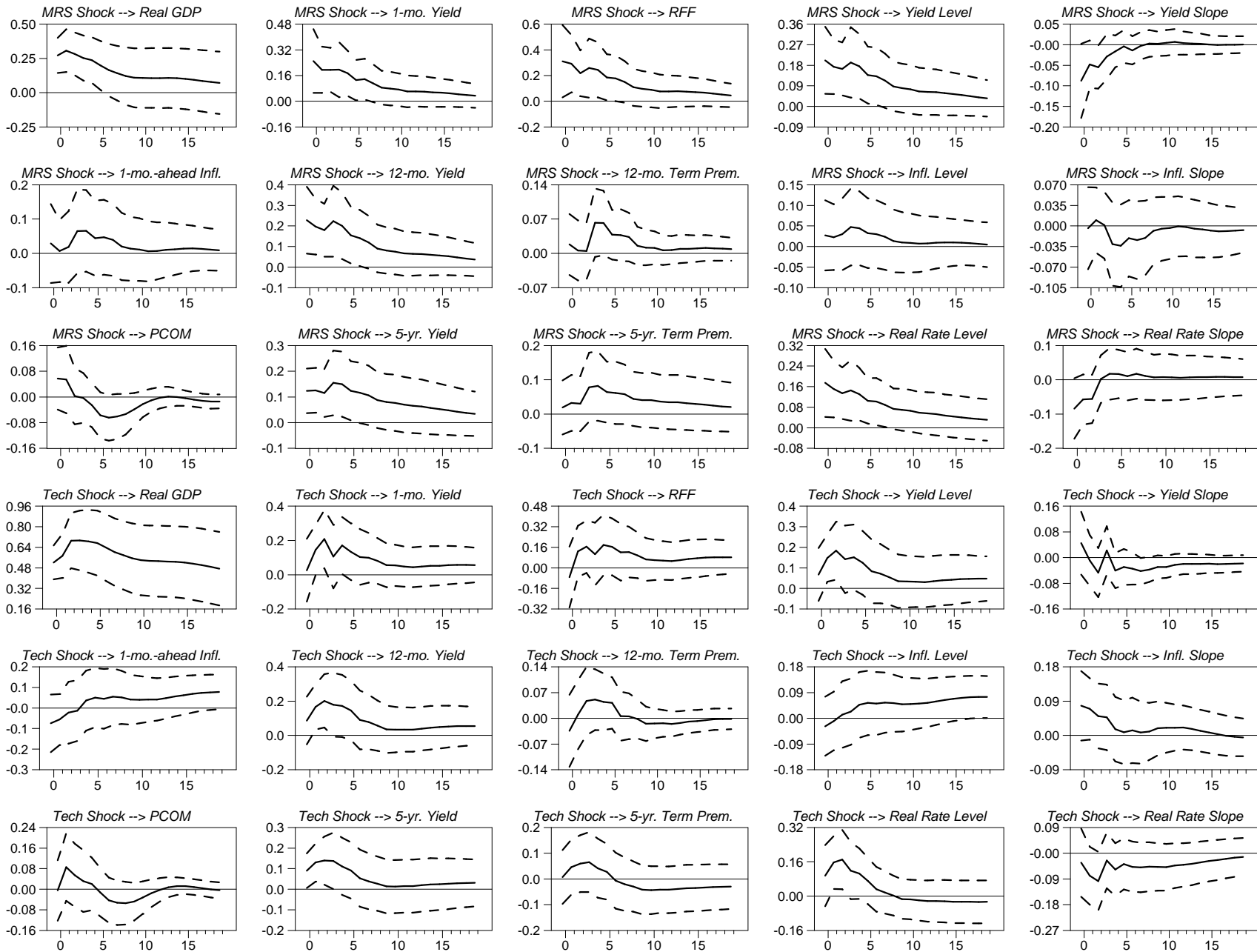


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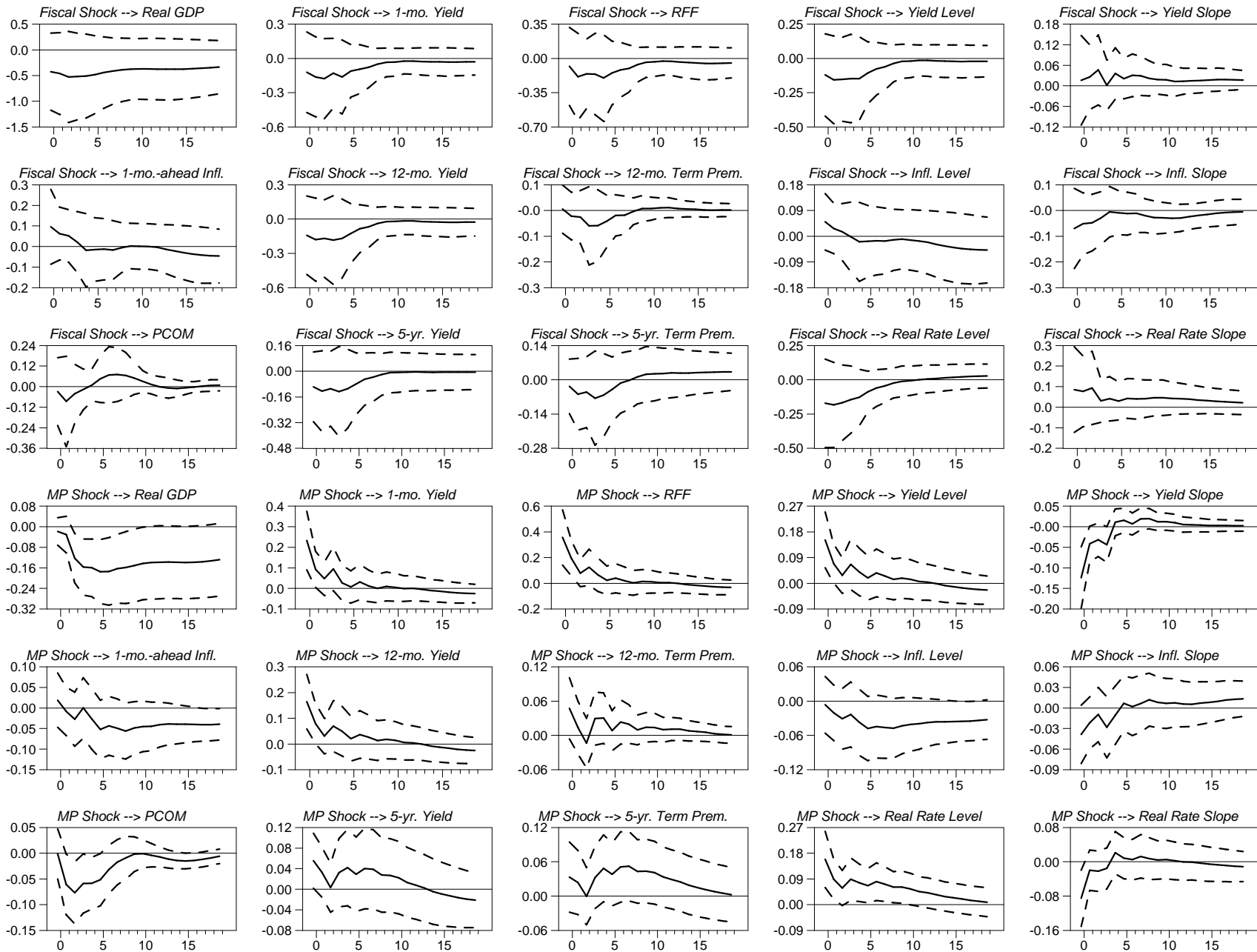


Figure 5: Exactly Identified VAR: Lower-Triangular D Matrix

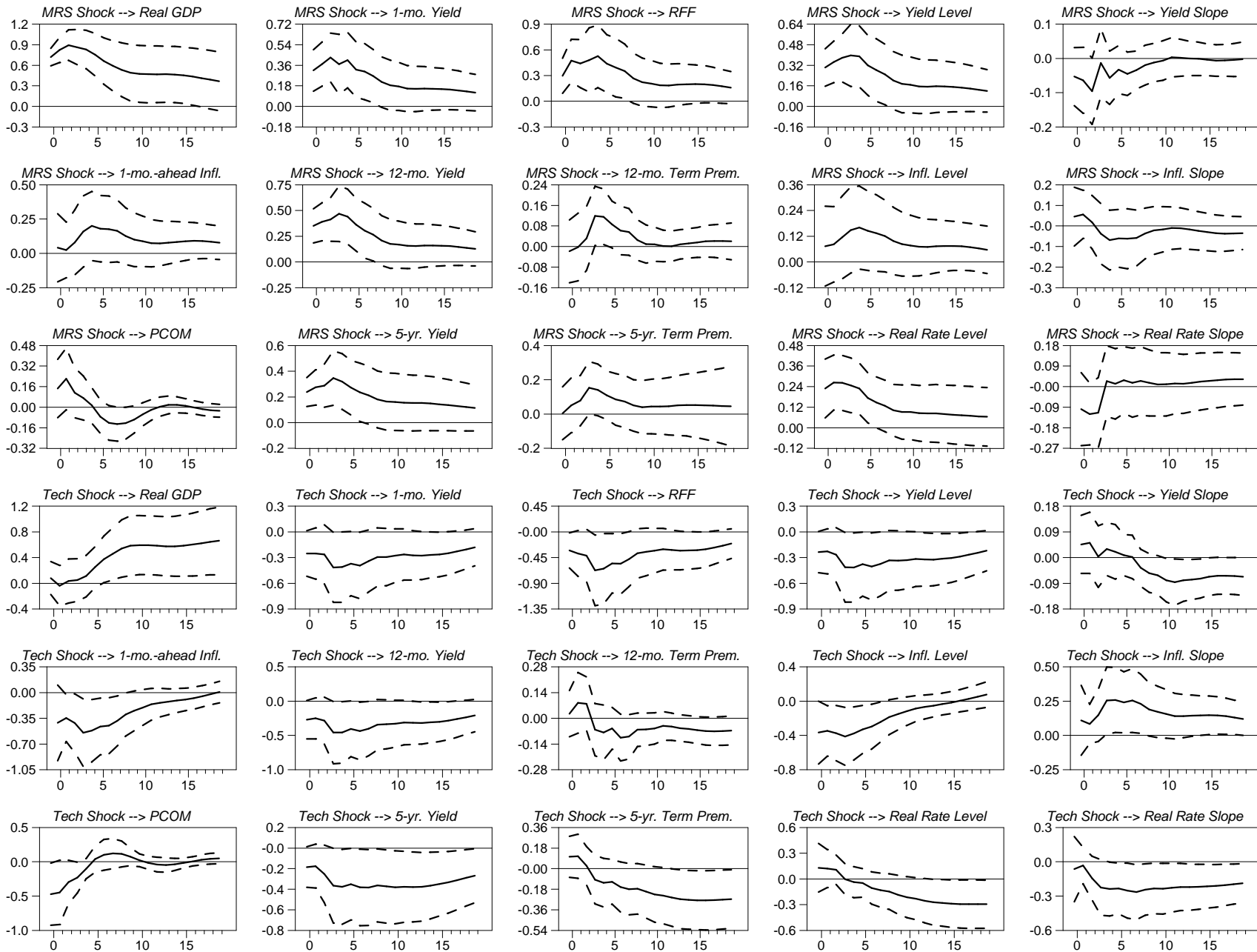


Figure 5 (continued)

