News Shocks and the Slope of the Term Structure of Interest Rates*

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Abstract

We provide a new structural interpretation of the relationship between the slope of the term structure of interest rates and macroeconomic fundamentals. We first adopt an agnostic identification approach that allows us to identify the shocks that explain most of the movements in the slope of the term structure of interest rates. We find that two shocks are sufficient to explain virtually all movements in the term structure slope. Impulse response functions for the first shock, which explains 70-90 percent of the movements in the slope, lead us to interpret this main shock as a news shock about future productivity. We confirm this interpretation by formally identifying such a news shock as in Sims (2009). We then assess to what extent a New Keynesian DSGE model is capable of generating the observed slope responses to a news shock. We find that augmenting DSGE models with a term structure provides valuable information to discipline the description of monetary policy and the model’s response to news shocks in general.

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1 Introduction

The slope of the term structure of interest rates has drawn the attention of many separate literatures. In the forecasting literature it is well established that movements in the slope of the term structure provides valuable predictive content for future economic activity. In a separate, but apparently related literature on macro-finance terms structure models, it has been established that shocks to the slope also drive macroeconomic variables. The slope also appears to play a role in monetary policy decisions. An important question arises from these literatures: Why are there movements in the slope of term structure and what can this teach us about both structural model building and monetary policy?

In this paper, we seek to uncover the fundamental sources of movements in the term structure slope without imposing strong (and potentially inappropriate) a priori identifying restrictions. Our contribution begins by combining the slope with prominent macro aggregates in a VAR. Based on this VAR, we apply a statistical criteria proposed by Uhlig (2003) to extract the one (or two) exogenous shock(s) that explain(s) as much as possible of the Forecast Error Variance (FEV) of a target variable in the VAR. We then search for possible interpretations of the extracted shock(s) using economic theory. It is important to note that nothing in our statistical approach requires that a small number of shocks are sufficient to account for a large part of term structure slope movements or that these shocks have an appealing macroeconomic interpretation. But since we find that a small number of shocks is sufficient to explain term structure slope dynamics, our exercise does provide valuable insights into the main determinants behind term structure slope movements.

Our estimates for the 1959-2005 period provide a number of number of intriguing results that are robust to different VAR and sample specifications. First, we find that one single shock explains between 70% and 90% of the unpredictable fluctuations in the term structure slope (i.e. the spread between long and short rates) over a 5-year horizon. Second, the slope shock closely resembles a news shock about future productivity as identified in Barsky and Sims (2009) and Sims (2009). To investigate this further, we apply their identification procedure of a news shock on our macro-finance VAR. This news shock is identified as the innovation that best explains future movements in total factor productivity (TFP) but is orthogonal to contemporaneous TFP innovations. Even though this identification procedure is completely different from our slope shock identification, we find that the shocks are highly correlated and generate remarkably similar impulse responses of macro aggregates. In particular, both shocks imply a persistent increase in the slope factor, driven primarily by a fall in the Federal funds rate. After an initial contraction of real activity and inflation, TFP, real activity as well as the stock market all turn significantly higher after about 2 years whereas the Federal Funds rate remains below its pre-shock values. Despite this loosening of monetary policy, inflation falls on impact of the shock and remains below trend for more than
two years. We thus conclude that the main driver of fluctuations in the slope of the yield curve are *news* about future innovations to productivity rather than *current* shocks to productivity or aggregate demand as imposed in recent macro-finance models.

In the second part of the paper, we build a New Keynesian DSGE model with news shocks and assess to what extent such a model is capable of generating the term structure movements to a news shock that we extracted from the VAR. Since term premia in our VAR are estimated to play a relatively small role for term structure movements in response to news shock, we limit our analysis to a standard log-linear version of the model, thus effectively imposing the expectations hypothesis of the term structure (EHTS); i.e. a version of the model with constant term premia. We find that a relatively simple version of the model generates responses of macro and term structure variables in line with the data. However, this fit depends crucially on the specification of monetary policy and the importance of frictions that are typically imposed on the model to match macro dynamics with respect to other shocks (e.g. Christiano et al., 2005; Smets and Wouters, 2007). In particular, our analysis reveals that interest rate rules responding to the output gap rather than output growth do not imply a sufficiently large and persistent drop in the short rate required to generate the observed increase in the term structure slope. Likewise, investment adjustment costs and variable capital utilization prevent the news shock from having a sizable contractionary effect on impact (e.g. Jaimovich and Rebelo, 2007). As a result, inflation remains relatively constant and monetary policy does not lower short rates, which again implies that the model fails to generate the observed increase in the term structure slope. This sensitivity of the model’s term structure implications with respect to otherwise uncontroversial assumptions illustrates the importance of including financial variables for the evaluation of macro models and suggests that the term structure slope provides valuable information for model identification.

Our empirical VAR approach presents an alternative to recent studies that attempt to bridge the gap between macro and finance explanations of the term structure. Studies such as Ang and Piazzesi (2003) or Diebold, Rudebusch and Aruoba (2006) combine term structure factors with macro variables in reduced-form linear models, an approach we also adopt in the first half of the paper. Both of these studies then impose a Cholesky orthogonalization to identify structural shocks. Such an ordering of course implies a timing restriction for which variables can respond to each shock. If financial markets respond to macro shocks within the period (and vice versa) then such restrictions are overly restrictive. More importantly, the shocks to the term structure factors are still difficult to interpret economically. For example, Diebold, Rudebusch and Aruoba conclude that shocks to a slope and level factor of their term structure model have important dynamic effects on macro variables. But this brings us back to one question we ask in this paper: do the shocks to these slope and level factors spring from more or less exogenous changes in asset markets or do they reflect innovations in macroeconomic fundamentals?
Another branch of the macro-finance literature is more explicit about the shocks that are identified. Evans and Marshall (2007) combine term structure and macro variables in a VAR. They then impose restrictions implied by structural macro models to identify different structural shocks. They conclude that technology shocks and shocks to preferences between consumption and leisure are both important sources of term structure fluctuations, mostly through the effect they have on systematic monetary policy responses. Exogenous fiscal and monetary shocks, by contrast, are found to play only a negligible role. Rudebusch and Wu (2008) and Bekaert, Cho and Moreno (2006), in turn, augment a small New Keynesian macro framework with a no-arbitrage model of the term structure. As in Evans and Marshall, both of these studies conclude that the yield curve has important macro and monetary underpinnings. However, because their identifying restrictions are different then Evans and Marshall (2007), the conclusion regarding the specific shocks that affect the term structure are also different. Both Rudebusch and Wu and Bekeart et al. conclude, for example, that the long end of the term structure is primarily driven by changes to the Federal Reserve’s implicit inflation target whereas monetary policy shocks are important drivers for variations in the slope of the yield curve.\footnote{There are many other examples in this now burgeoning literature. Other studies with similar small structural macro-finance models are Gurkanyak, Sack and Swanson (200x), Hordahl, Tristani and Vestin (2006) or Dai and Philippon (200x).}

The remainder of the paper proceeds as follows. Section 2 explains our empirical approach. This section discusses both the Uhlig (2003) FEV shock identification as well as the Sims (2009) news shock identification. Section 3 provides information about the data while Section 4 presents our empirical results for both the Uhlig FEV identification of shocks and the news identification. Section 5 builds and analyzes the DSGE model with both a terms structure and news shocks. Section 6 concludes.

2 Shock Identification: Two Approaches

Our objective in this paper is to first understand the sources of movements in the term structure slope and to then provide a structural model consistent with the empirical results. In this section we outline two approaches to VAR identification. The first is an agnostic procedure which identifies the largest 1 or 2 (or 3 or 4) shocks that explain the maximal amount of the forecast error variance (FEV) in a target variable (e.g. Uhlig 2003). Here are target variable will be the slope of the term structure as measured by the difference between long and short term yields. At this stage the identification is purely statistical. We then observe what this shock does to the other macroeconomic variables. This allows us to interpret the shock. The agnostic identification procedure suggests that news about productivity plays an important role in explaining movements in the slope. To refine
this interpretation we extend our analysis to formally identify news shocks. The news shocks are identified by placing extra restrictions on the FEV identification following Sims (2009). For this second VAR we use productivity as the target variable.

This section first covers the general issue of identifying shocks in a VAR framework. This issue is well known and we present these results both for completeness and because the notation is useful for understanding both the Uhlig (2003) and Sims (2009) procedures. Section 2.1 presents the general VAR results. Section 2.2 presents the Uhlig (2003) identification scheme while 2.3 presents the Sims’ (2009) identification of news shocks. These results will be applied in subsequent sections of the paper.

2.1 Identifying VAR Shocks

We begin with a reduced-form VAR of the form:

\[ Y_t = B_1Y_{t-1} + B_2Y_{t-2} + \ldots + B_pY_{t-p} + u_t \]  

where \( Y_t \) is a \( mx1 \) vector of variables observed at time \( t \), and \( u_t \) is a \( mx1 \) vector of one-step-ahead prediction errors with variance-covariance matrix \( E[u_tu'_t] = \Sigma \). Constant terms have been dropped to conserve notation. The goal of identification is to impose restrictions on equation (2) to identify the structural shocks. Traditionally, one imposes \( m(m-1)/2 \) restrictions on the VAR model (2) to identify all \( m \) shocks in the VAR system. Though this is the traditional approach to identification, we will see below that one can identify fewer than \( m \) shocks.

In order to more clearly see the identification issue it is useful to rewrite equation (2). Under the assumption that \( Y_t \) is covariance-stationary, we can invert this VAR to express it as a moving average process:

\[ Y_t = [B(L)]^{-1}u_t = C(L)u_t, \]  

where \( B(L) \equiv I - B_1L - \ldots - B_pL^p \), and \( C(L) \equiv I + C_1L + C_2L^2 + \ldots \)

This moving average representation is of course the impulse response function for the VAR. Identification of the structural shocks amounts to decomposing the vector of prediction errors \( u_t \) into \( m \) mutually orthogonal innovations \( v_t \) with normalized variance-covariance matrix \( E[v_tv'_t] = I \). In other words, in identifying VAR shocks we are trying to find a mapping, \( A \), between the reduced form and structural shocks. The mapping, \( u_t = Av_t \) implies that the VAR can be re-written as:

\[ Y_t = C(L)Av_t. \]  

In this mapping the \( i \)-th column of the \( mxm \) matrix \( A \) thus describes the contemporaneous effect of the \( i \)-th innovation in the structural shock vector, \( v_t \), on the different variables in \( Y_t \). By definition, \( A \) needs to satisfy \( \Sigma = E[Av_tv'_tA'] = AA' \). This restrictions, however, is not sufficient to
identify $A$ because for any matrix $A$, there exists some other matrix $\tilde{A}$ that satisfies the restriction that the covariance matrix be respected. This alternative matrix provides a different map from $u_t$ into $\tilde{v}_t$, i.e. $u_t = \tilde{A}\tilde{v}_t$. To see this, consider an orthogonal matrix $Q$ with $QQ' = I$ and define $A = \tilde{A}Q$ and $Qv_t = \tilde{v}_t$. Then, $\Sigma = E[\tilde{A}Qv_t\tilde{v}_tQ'] = E[\tilde{A}\tilde{v}_t\tilde{v}_t'\tilde{A}'] = \tilde{A}\tilde{A}'$ because $E[\tilde{v}_t\tilde{v}_t'] = QE[v_tv_t']Q' = QQ' = I$. Thus the set of statistically valid 'structural' identifications of the VAR is quite large. To choose which identification restriction to use one then typically uses some sort of economic theory. One prominent example is to use a Cholesky decomposition and restrict $A$ to be lower triangular. Economically, this amounts to ordering the variables in the VAR in terms of the timing with which variables can respond to various structural shocks.

2.2 Finding the Largest Shock(s)

An alternative to the more traditional approach and identifying all shocks is to follow Uhlig (2003). This approach to identification is purely statistical and consists of finding the innovation(s) that explain(s) as much as possible of the forecast error variance of some variable in $Y_t$ over a chosen horizon $k$ to $\tilde{k}$. The first thing one learns from this procedure is how many shocks are needed to explain a given variable. That is, do we need a large scale DSGE model with many shocks, or will a more parsimonious model be able to explain a given time series? After identifying the largest shock one then studies the full set of impulse response functions to provide an economic interpretation of the shocks.

More precisely, we will search for the $n$ largest shocks to explain the FEV of one variable in the VAR. Thus we need to find the $mxn$ submatrix $A_1$ for the $n$ most important innovations in $v_t$ such that $A = [A_1 \ A_2]$ with $AA' = \Sigma$ for some other $mx(m-n)$ submatrix $A_2$. Given some decomposition $\tilde{A}$, this amounts to computing $A_1 = \tilde{A}Q_1$ where $Q_1$ is the $nxm$ partition $Q_1$ of $Q = [Q_1 \ Q_2]$ that satisfies our statistical criteria.

To find $Q_1$, we let $\tilde{A}\tilde{A}' = \Sigma$ be the Cholesky decomposition of the reduced for VAR covariance matrix. We define the impulse responses $\tilde{R}(L)$ associated with the innovations $\tilde{v}_t$ identified by this decomposition as

$$\tilde{R}(L) = C(L)\tilde{A}.$$ 
$$= \tilde{R}_0 + \tilde{R}_1L + ...$$

with $\tilde{R}_0 = \tilde{A}$. The impulse responses associated with the targeted innovations $v_t$ are thus given by

$$R(L) = C(L)\tilde{A}Q = \tilde{R}(L)Q.$$ 

\footnote{Any other triangular factorization would do as well, but the Cholesky is particularly easy to implement.}
The $k$-step ahead forecast error of $Y_{t+k}$ is then given by

$$u_{t+k}(k) = Y_{t+k} - E_{t-1}[Y_{t+k}] = \sum_{l=0}^{k} \tilde{R}_t v_{t+k-l},$$

and its variance-covariance matrix is given by

$$\Sigma(k) = \sum_{l=0}^{k} \left( \tilde{R}_t[q_1 q_2 \ldots q_m] \right) \left( \tilde{R}_t[q_1 q_2 \ldots q_m] \right)'$$

$$= \sum_{l=0}^{k} \left[ (\tilde{R}_t q_1)(\tilde{R}_t q_1)' + (\tilde{R}_t q_2)(\tilde{R}_t q_2)' + \ldots + (\tilde{R}_t q_m)(\tilde{R}_t q_m)' \right]$$

$$= \sum_{j=0}^{m} \sum_{l=0}^{k} (\tilde{R}_t q_j)(\tilde{R}_t q_j)'$$

where $q_i, i = 1 \ldots m$ are the $m \times 1$ column vector partitions of $Q$. The term $\sum_{l=0}^{k} (\tilde{R}_t q_j)(\tilde{R}_t q_j)'$ thus describes the contribution of the $j$-th orthogonal shock to the variance-covariance matrix $\Sigma(k)$ of the $k$-step ahead forecast error $u_{t+k}(k)$. This division into $m$ parts is possible because the $v_t$ are iid innovations and the columns $q_i, i = 1 \ldots m$ are orthogonal.

Our objective is to find the innovation(s) that explains as much as possible of the sum of the $k$-step ahead forecast error variance of the $i$-th variable in $Y$ over some horizon $k \leq k \leq \tilde{k}$:

$$\sigma_i^2(k, \tilde{k}) = \sum_{k=k}^{\tilde{k}} \Sigma(k)_{ii}.$$ 

Formally, we want to find the orthogonal vector $q_1$ with length 1 that maximizes\(^3\)

$$\sigma_i^2(k, \tilde{k}; q_1) = \sum_{k=k}^{\tilde{k}} \sum_{l=0}^{k} \left[ (\tilde{R}_t q_1)(\tilde{R}_t q_1)' \right]_{ii}$$

$$= \sum_{k=k}^{\tilde{k}} \sum_{l=0}^{k} \text{trace} \left[ E_{(ii)}(\tilde{R}_t q_1)(\tilde{R}_t q_1)' \right]$$

$$= \sum_{k=k}^{\tilde{k}} \sum_{l=0}^{k} \text{trace}(\tilde{R}_t^l E_{(ii)} \tilde{R}_t),$$

where $E_{(ii)}$ is a matrix with zeros everywhere except for the $i, i$-th position, and where the last line makes use of the fact that for any square matrices $A$, $B$ and $C$, we have $\text{trace}(ABC) = \text{trace}(CAB)$. Since $\sum_{k=k}^{\tilde{k}} \sum_{l=0}^{k} \text{trace}(\tilde{R}_t^l E_{(ii)} \tilde{R}_t)$ is a scalar and $q_1 q_1' = 1$, we can rewrite this object as

$$\sigma_i^2(k, \tilde{k}; q_1) = q_1' S q_1,$$

\(^3\)For notational convenience, we order this vector first in $Q$. 

with
\[
S = \sum_{k=0}^{k} \sum_{l=0}^{k} \tilde{R}_i^l E_{(ii)} \tilde{R}_l \\
= \sum_{l=0}^{k} (\tilde{k} + 1 - \max(k, l)) \tilde{R}_i^l E_{(ii)} \tilde{R}_l.
\]

Our maximization problem subject to \(q_1^q q_1 = 1\) can thus be written as a Lagrange optimization problem:
\[
L = q_1^q S q_1 - \lambda (q_1^q q_1 - 1)
\]
with first-order condition
\[
S q_1 = \lambda q_1.
\]

Inspection of this solution reveals that this is simply the definition of an eigenvalue decomposition, with \(q_1\) being the eigenvector of \(S\) that corresponds to the eigenvalue \(\lambda\). Furthermore, since \(q_1^q q_1 = 1\), we can rewrite the first-order as \(\lambda = q_1^q S q_1 = \sigma_1^2 (k, k; q_1)\). The partition \(q_1\) that maximizes the variance is therefore the eigenvector associated with the largest eigenvector \(\lambda\); i.e. \(q_1\) is the first principal component of \(S\). Likewise, \(q_2\) is the second principal component and so forth for all the \(n\) components of \(Q_1\) that we want to extract. The submatrix \(A_1\) that seek is then:
\[
A_1 = \tilde{A} Q_1.
\]

### 2.3 Identifying News Shocks

The news shock that we seek to identify is news about future productivity, following Sims (2009). In his procedure productivity is placed in a VAR with a selection of other macroeconomic variables. The assumption underlying the identification procedure is that productivity is an exogenous process. Therefore shocks to other variables in the system, such as monetary policy shocks, will not impact productivity at any horizon. Productivity then is driven by two shocks. One is an unforecastable shock to current productivity, and the second is a shock that represents news about future productivity.

The Sims news shock identification can be interpreted as an additional restriction on the Uhlig FEV identification. To implement the procedure we choose productivity as the variable in the VAR for which we would like extract the shocks to maximize the FEV explained. Further, the number of shocks we seek to identify is restricted to two (i.e. \(n = 2\) in section 2.2). We then impose two additional restriction on the Lagrangian in (11). First, the news shock must have zero impact on productivity contemporaneously. Second, the two technology shocks, the news shock and innovation to current productivity, must explain all of the movements in future productivity. A
news shock then, is the innovation that explains future movements in productivity but not current movements. At any point in time productivity moves for three reasons. First, there may be current innovations to productivity. Second, past productivity innovations propagate forward. Third, past news shocks are realized as subsequent movements in productivity.

3 Data

To calculate the term spread we use the 60 month yield from the CRSP government bonds file. We convert the monthly yield data to quarterly frequency since most of our VAR analysis is with quarterly macro data. We use as the short rate the federal funds rate. A second option would be to use the 1 month treasury yield. We use the federal funds rate since it corresponds to the spread in the DSGE model in the second half of the paper.

For the macro data, the real variables are all from the BEA’s NIPA accounts. These include real GDP, consumption, investment, and hours worked. Inflation and the federal funds rate are taken from the St. Louis Fed’s FRED database. The series of corrected TFP is from Sims (2009). The real S&P composite index is taken from Robert Shiller’s website.

4 What Moves the Slope of the Term Structure?

In this section we begin by estimating a VAR with the term structure slope, real GDP, consumption, investment, inflation, real stock returns, hours worked and productivity. The VAR includes 4 lags of each variables. To improve precision we impose a Minnesota prior when estimating the VAR. We find the two largest shocks to explain movements in the slope factor, which is our ‘target’ variable in this VAR. To do so we maximize the percent of forecast error variance over the horizon zero to twenty quarters. Our strategy is to first assess the extent to which the two shocks we extract are quantitatively important. We do this by examining the forecast error variance decomposition.

4.1 Variance decomposition and Impulse Response Functions

Figures 1 displays the variance decomposition for the first shock that explains most of the FEV of the slope. In terms of FEV, the shock explains about 85 percent of the slope movements on impact and about 70 percent after 20 quarters. It also explains about 25 percent of hours, investment and the deflator and around 50 percent of funds rate. For TFP, the shock explains virtually nothing on impact and then gradually explains more (with about 20-30 percent after 20Q). We conclude that the first shock we have extracted is responsible for much of the movements in the slope factor. The second factor, is less important, but when taken together the two shocks explain virtually all of the movements in the slope. A result of this exercise is that additional shocks are not needed to
understand movements in the term structure and to a first approximation, only one shock is very relevant.

We now provide an economic interpretation of the shocks by examining the impulse response functions of all variables to both the slope and level shock. Figure 2 displays the IRFs to the first shock that explains the majority of the slope FEV. The slope jumps up on impact of the shock, whereas the long end of the term structure remains roughly constant on impact before becoming negative. The increase in the slope is thus mainly due to the drop in the short end of the term structure, triggered by the drop in the federal funds rate. Interestingly, the effect of the shock on real activity is also negative on impact and only becomes positive after more than a year. The slope shock thus appears related to economic activity at least in a quantitative sense. This is consistent with the literature that movements in the slope help explain future real activity. Lastly, consider inflation, which drops on impact and remains below its initial level for more than 2 years.

How do we interpret this shock? Given the negative response of both real activity and the price level in conjunction with the drop in the federal funds rate, the shock does not resemble an exogenous monetary policy intervention. Rather, monetary policy reacts endogenously to the shock and is thus, indirectly, the main driver of the slope (since slope movements are mostly driven by the short end of the term structure). It appears that this shock is the federal reserve responding to what it perceives to be a weakness in real activity as TFP initially declines. However, after an initial contraction of real activity and inflation, TFP, real activity as well as the stock market all turn significantly higher after about 2 years whereas the Federal Funds rate remains below its pre-shock values. Despite this loosening of monetary policy, inflation remains significantly lower. The response of the core macro variables is very much like the news shock in Sims (2009). In the next section we will investigate this interpretation further in greater detail.

Since the interpretation of shocks in Uhlig’s (2003) is somewhat subjective it is useful to also consider why other prominent shocks are not slope shocks. The shock is not a monetary policy shock because of the behavior of inflation. After an expansionary monetary policy shock inflation should rise. Here, inflation falls so we rule out a monetary shock explanation. Productivity is a second common driver of macro variables. Here, productivity does not move on impact which rules it out as an interpretation of our slope shock. A third type of shock often consider is a demand shock. Since consumption does not move on impact (and inflation falls) we can rule out a demand shock interpretation of our slope shock. We have also considered a VAR with oil in it (not shown for space reasons) and oil shocks can also be ruled out.

4.2 Slope Shocks are News Shocks

As suggested in the previous section the slope shock in section 4 looks similar to the news shock identified in Sims (2009). In figure 3 we formally identify a news shock following Sims (2009).
Sims’ VAR contains fewer variables than ours, but for the variables in common the similarity in the IRF is clear. This motivates us to identify a news shock following Sims (2009) but using our VAR with the term structure slope. The difference between the approach we use to identify the news shock and the identification of the largest shock in the previous section is quite significant. The news shock is extracted by searching directly for the shock that explains future productivity movements (subject to the restrictions in section 3) while our previous shocks were extracted to explain movements in term structure factors. A priori, there is no reason to think that the shocks extracted for the different VARs will be strongly related, but as we will see, they are.

Figure 4 contains the impulse response functions for the response to the news shock along with the Slope shock for comparison. For most variables they are similar to Sims’ results and consistent with a story about news about future productivity. We see that TFP (which has a zero response on impact by construction) responds positively to the shock, as do GDP, consumption and investment. Surprisingly, the Federal Reserve responds by lowering interest rates, an expansionary policy. The Federal Reserve appears to be justified in such a response as the news shock is not inflationary. In fact, inflation falls over the period. This is consistent with the view in the Greenspan era that rising future productivity (mostly due to improvements in computers) meant that it was safe to have an expansionary policy.

The main difference between the slope shock we extract and the news shock is that productivity falls on impact with the slope shock. This fall however, is short lived. To confirm our interpretation of the slope shock as a news shock we extract the time series of the two shocks from the two VARs. Figure 5 plots the two time series and clearly the shocks move together. In fact, the correlation between the two shock time series is 0.8.

4.3 Time-varying term premia versus the Expectations Hypothesis

An important remaining question is to what extent the movements in the long rate and thus the slope reflect variations in term premia rather than expectations about future short rates. In fact, the modern DSGE literature working in a loglinear context simply assumes that term premia are constant (e.g. Rudebusch, Sack and Swanson, 2007). By contrast, a large finance literature finds that term premia are substantial and vary significantly over time (e.g. Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005).

The difficulty with answering this question is that term premia are inherently unobservable. Here, we follow Campbell and Shiller (1987, 1991) and take our VAR as a forecasting process for future short rates to compute the long rate as implied by the expectations hypothesis. The difference between the observed long rate and the long rate implied the expectations hypothesis then represents the term premium. Figures 6 and 7 show the resulting decomposition (as well as a decomposition of the expectations hypothesis into a real part and an inflation part) for the Uhlig
shock and the news shock, respectively.

For the slope shock, the long rate under the expectations hypothesis drops on impact of the shock before slowly returning to its initial value. As a result, the term premium increases significantly on impact. The responses to the news shock are similar, only that now, the increase in the term premium on impact is smaller and no longer significant.\textsuperscript{4} Note, however, that even in the case of the Uhlig shock, the variation in term premium is not large enough to account for the entire movement in the slope. We conclude from this decomposition that, while term premia do have some quantitative importance, the expectations hypothesis by itself can account for a sizable fraction of the slope movements in response to a news shock.

5 A DSGE-News Model of the Term Structure

In this section, we evaluate to what extent a DSGE model can account for the response of the term structure slope after a news shock. Given our above conclusion that variations in term premia are relatively small (and insignificant) in response to news shocks, we confine our analysis to a loglinear model where, by assumption, term premia are constant; i.e. the Expectations Hypothesis holds.

5.1 Model

We adopt a fairly standard medium-scale New Keynesian model and add to it news shocks and the expectations hypothesis to price the long term bond. This bond allows us to calculate the slope of the term structure of interest rates and to compare it to our VAR results. The model is a combination between the model presented in Altig, Christiano, Eichenbaum and Linde’s (2004; ACEL) and Smets and Wouters (2007). The full model equations are presented in the appendix. The model features a permanent TFP shock as well as a number of commonly used frictions. The main structural difference of our model from ACEL is that we abstract from their transactions-based money demand and replace their money growth rule with a more standard interest rate rule.\textsuperscript{5} The main structural difference with the model in Smets and Wouters (2007) is that our technology shocks feature a stochastic trend and that we consider a somewhat more general interest rate rule.

A second important departure of our model from both ACEL and Smets and Wouters is that we allow for an exogenous shock that represents news about future total factor productivity (e.g.\textsuperscript{4}This difference in term premia variation matches well with the intuition that term premia compensate for inflation risk (e.g. Rudebusch and Swanson, 2009). Specifically, long term bonds are risky in periods when inflation and real growth fluctuate inversely as is the case after our news shock. From Figure 4, we know that inflation drops less after the news shock than after the slope shock, which explains why the term premium required to compensate for inflation risk is smaller for the news shock.\textsuperscript{5}We also abstract from firm-specific capital. In a loglinearized framework, this only changes the mapping from the price rigidity parameter to the marginal cost slope in the New Keynesian Phillips curve.)
Schmidt-Grohe and Uribe 2008, Sims 2009, Jaimovich and Rebelo 2009). Specifically, we let TFP growth evolve according to

\[ \dot{\mu}_A = \rho_{\mu_A} \mu_{A,t-1} + \varepsilon_{\mu_A} + \varepsilon_{\mu_A,t-j} \quad \text{with} \quad \varepsilon_{\mu_A,t} \sim iid \left(0, \sigma_{\varepsilon_{\mu_A}}^2\right) \]

where \( \varepsilon_{\mu_A} \) is the contemporaneous shock; and \( \varepsilon_{\mu_A,t-j} \) is the news shock that occurs \( j \) periods in advance.

Since we are interested in the slope of the term structure, we need to price a long term bond. We follow De Graeve, Emiris and Wouters (2009) and impose the expectations hypothesis in our loglinearized framework. The yield on the \( T \)-period zero-coupon bond is thus

\[ \hat{R}^T_t = \frac{1}{T} E_t \left[ \hat{R}_t + \hat{R}_{t+1} + ... \hat{R}_{t+T-1} \right] \]

where \( \hat{R}_t \) is the yield on a 1-period bond between \( t \) and \( t+1 \).

Finally and as already mentioned above, we work with a relatively general specification for monetary policy

\[ \hat{R}_t = \rho_R \hat{R}_{t-1} + (1 - \rho_R) \left[ \theta_\pi E_t \hat{\pi}_{t+1} + \theta_{\text{ygap}} \hat{y}_{gap,t} + \theta_{\text{\Delta y}} \Delta \hat{y}_t \right] + \theta_{\text{\Delta ygap}} \Delta \hat{y}_{gap,t} \]

where \( \hat{y}_{gap,t} = \hat{y}_t - \hat{y}_{flex,t} \) is the output gap and \( \Delta \hat{y}_t \) is the growth rate of output. For \( \theta_{\text{\Delta y}} = 0 \) and \( E_t \hat{\pi}_{t+1} \) replaced by \( \hat{\pi}_t \), this specification collapses to the one used by Smets and Wouters (2007).

### 5.2 Calibration

We consider three different versions of our model:

1. A simplified version of the model without investment adjustment costs (i.e. \( \chi = 0 \)), constant capital utilization (i.e. \( \sigma_u = \infty \)) and a monetary policy rule that responds to expected inflation and output growth only (i.e. \( \theta_{\text{ygap}} = \theta_{\text{\Delta ygap}} = 0 \)).
2. The same simplified version of the model but with a monetary policy rule that responds to expected inflation and the output gap instead of output growth (i.e. \( \theta_{\text{\Delta y}} = 0 \)).
3. A complete version of the model with investment adjustment costs, variable capital utilization and a monetary policy rule that responds to both the current and lagged output gap (i.e. \( \theta_{\text{\Delta y}} = 0 \)).

Table 1 shows the different calibrations, which all pertain to quarterly data.
For the first version of the model, we calibrate the different structural parameters in line with different estimates in the literature (except for investment adjustment cost and capital utilization), and arbitrarily set the monetary policy rule so as to achieve as good of an overall fit as possible. For the second version of the model, we keep the same calibration and simply change the description of monetary policy so as to illustrate the sensitivity of the model to this relatively small difference in specification. For the third model, we recalculate all parameters to the median estimates reported in Smets and Wouters’ (2007). Note that with the exception of the parameters for investment adjustment cost and capital utilization (i.e. $\chi$ and $\sigma_u$) and the specification of monetary policy, the calibration of the other parameters is relatively similar to the one for the first two versions of the model.

Finally, the news shock in all three versions of the model is calibrated so as to generate exactly the response of TFP to the news shock observed in the VAR. We find that $\varphi = 1$, $\rho_{\mu_A} = 0.8$ and $\sigma_{\epsilon_{\mu_A}} = 0.07$ does an excellent job in achieving this objective.
5.3 Impulse response functions to a news shock

Figure 8 displays the impulse responses to a news shock for version 1 of the model. On the real side, the model does a surprisingly good job in matching the response of output and hours but falls somewhat short of generating the significant increase in consumption and inflation after one to two years of the news shock. On the monetary side, the model almost perfectly matches the inflation and spread response but does not quite generate the drop in either the federal funds rate, the observed long rate (bottom left panel) or the long rate under the EHTS (bottom right panel). Given that term premia are constant by definition in this model, the failure to match the observed long rate is not all that surprising.

The model could be made to match both the fed funds rate and the long rate under the EHTS more closely by tinkering around with the different monetary policy parameters. However, this is not the point here. Rather, we want to illustrate with this first simulation that a relatively simple New Keynesian DSGE model is capable of generating macro and term structure dynamics in response to a news shock that are, on average, relatively close to the ones extracted from the VAR. Given this benchmark, we now show with the second and third simulation that this performance is highly sensitive to relatively minor model changes.

Figure 9 displays the impulse responses to a news shock for version 2 of the model. The only aspect changed relative to version 1 is the monetary policy where we exchanged output growth with the output gap. Yet, the model dynamics to the news shock are dramatically changed. Output, hours and investment drop several percentage points on impact of the news and then shoot into positive territory in period 2 when the TFP shock realizes. Inflation also drops on impact and then shoots up as the economy expands. The response of the Fed funds rate, in turn, is only slightly positive. As a result, the long rate does not fall and the spread barely reacts. Hence, the model now fails dramatically at getting anything about the news shock right. Intuitively, the reason for this change is that the output gap reacts very differently in response to a news shock than output growth. In fact, potential output (i.e. the output that would pertain in the absence of nominal rigidities) is always below actual output when prices fall because without nominal rigidities, markups remain constant whereas with rigidities they decrease. The output gap thus jumps up on impact of the news shock whereas output growth falls. In response, monetary policy does not accommodate the news shock, which explains the absence of the fall in the Fed funds rate.

Figure 10, finally, displays the impulse responses for version 3 of the model. The model now completely fails to generate the initial contraction of the economy after the news shock that we see in the VAR. As a consequence, neither the fed funds rate nor the long rate falls and the spread barely reacts. Again, these impulse responses are dramatically different from the ones found above. The main reason for this change is the introduction of investment adjustment cost and variable
capital utilization. As Jaimovich and Rebelo (2009) show, the investment adjustment cost friction mitigates the drop in investment whereas variable capital utilization helps the economy cope with the larger demand implied by consumption smoothing. Jaimovich and Rebelo (2009) interpret both of these effects as positive because they allow the model to generate macro dynamics to news shock in line with the VAR responses in Beaudry and Portier (2004). The problem is, as shown by Barsky and Sims (2009) and Sims (2009), that a news shock identification directly on TFP is completely opposite from Beaudry and Portier’s (2004) results and call into question the importance of news shocks as a main driver of business cycle fluctuations. Our results here confirm this conclusion and show, in addition, that a model with investment adjustment cost and variable capital utilization also fails to generate term structure dynamics in line with the data. In our opinion, this raises an important challenge for business cycle modeling because both of these frictions are estimated to be significant ingredients for macro dynamics conditional on more standard shocks.

6 Conclusion

TBA

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6 Note that very similar dynamics would pertain if monetary policy was described as in version 1 of the model.
References


7 Appendix: New Keynesian Model

The loglinearized equations of the New Keynesian model are (hatted variables describe log-deviations from steady states of the normalized variables)

\[
\begin{align*}
\hat{\xi}_t &= \frac{\beta}{g_K} E_t \left[ k^* \hat{\lambda}_{t+1} + \hat{\lambda}_t + \left( 1 - \delta \right) \hat{\Delta}_{t+1} \right] - E_t (\hat{\mu}_{At+1} + \frac{1}{\alpha} \hat{\mu}_{VT+1}) \\
\hat{\lambda}_t &= \hat{\xi}_t - \chi g_C^2 (\hat{\Delta}_t - \hat{\mu}_{At} + \frac{1 - \alpha}{\alpha} \hat{\mu}_{VT} - \hat{\mu}_{GT}) + \beta \chi g_C^2 E_t \left[ \hat{\Delta}_{t+1} - \hat{\mu}_{At+1} + \frac{1 - \alpha}{\alpha} \hat{\mu}_{VT+1} \right] \\
\hat{k}_{t+1} &= \frac{1 - \delta}{g_K} \left[ \hat{k}_t - \frac{\delta' (u \hat{\Delta}_t)}{\delta' (u)} \hat{\Delta}_t - \frac{1}{\alpha} \hat{\mu}_{VT} \right] + \hat{\mu}_{At+1} \\
\hat{R}_t + \hat{\omega}_t &= \hat{\psi}_t + \hat{\eta}_t - \hat{\mu}_t \\
\hat{\omega}_t &= \hat{\psi}_t + \hat{\eta}_t - \hat{\mu}_t \\
(1 + \sigma_u) \hat{\omega}_t &= (1 + \frac{\delta'' (u \hat{\Delta}_t)}{\delta' (u)}) \hat{\Delta}_t = \hat{\omega}_t \\
\hat{\eta}_t &= \alpha \hat{\Delta}_t + (1 - \alpha) \hat{\Delta}_t + \frac{\alpha - 1}{\alpha} \hat{\mu}_{VT+1} \\
\hat{\mu}_t &= \hat{\Delta}_t + \frac{1 + \eta (v)}{\hat{\mu}_{At+1}} \hat{\Delta}_t + \eta (v) \hat{\Delta}_t \\
(1 + \omega_p \beta) \hat{\pi}_t &= \beta E_t \hat{\pi}_{t+1} + \omega_p \hat{\pi}_{t-1} + \kappa \hat{\psi}_t \\
\hat{\xi}_t &= E_t \left[ \hat{\lambda}_t + \frac{1 - \alpha}{\alpha} \hat{\mu}_{VT+1} \right] + \hat{\Delta}_t - E_t \hat{\pi}_{t+1} \\
\hat{\psi}_t &= \hat{\xi}_t - \hat{\mu}_t \\
\hat{\omega}_t &= \frac{\mu_{Mt} m (\hat{\mu}_t + \hat{\omega}_t) - q \hat{\omega}_t}{\mu_{Mt} m - q} \\
\hat{\mu}_t &= \frac{\mu_{Mt} m (\hat{\mu}_t + \hat{\omega}_t) - q \hat{\omega}_t}{\mu_{Mt} m - q} \\
0 &= \eta_1 \hat{\omega}_t + \eta_2 \hat{\omega}_t + \eta_3 \hat{\pi}_t + \eta_4 \hat{\pi}_t + \eta_5 \hat{\pi}_t + \eta_6 \hat{\pi}_t + \eta_7 \hat{\lambda}_t + \eta_8 \frac{\alpha}{1 - \alpha} \hat{\mu}_{VT+1} + \eta_9 \frac{\alpha}{1 - \alpha} \hat{\mu}_{VT+1} + \eta_{10} \frac{1}{1 - \alpha} \hat{\mu}_{VT+1} + \eta_{11} \hat{\mu}_{VT+1},
\end{align*}
\]
where

\[
\begin{pmatrix}
\eta_0 \\
\eta_1 \\
\eta_2 \\
\eta_3 \\
\eta_4 \\
\eta_5 \\
\eta_6 \\
\eta_7 \\
\eta_8 \\
\eta_9 \\
\end{pmatrix} =
\begin{pmatrix}
b_w \xi_w \\
-b_w [1 + \beta \xi_w^2] + (\eta_L - 1) \lambda_w \\
\beta \xi_w b_w \\
b_w \xi_w \varphi_w \\
-b_w \xi_w [1 + \varphi_w \beta] \\
b_w \xi_w \beta \\
-(\eta_L - 1)(1 - \lambda_w) \\
1 - \lambda_w \\
-b_w \xi_w \\
b_w \xi_w \beta \\
\end{pmatrix}
\]

with \( b_w \equiv \frac{(\eta_L - 1) \lambda_w - (1 - \lambda_w)}{(1 - \beta \xi_w)(1 - \xi_w)} \). Since the model contains permanent technology and monetary shocks, all the variable here are normalized appropriately.

Monetary policy takes the form of either a money growth rule or an interest-rate rule. The money growth rule is

\[
\hat{\mu}_{Mt} = \hat{\mu}_{M^*t} + \phi_A \mu_A + \phi_V \frac{1 - \alpha}{\alpha} \hat{\mu}_{Vt}
\]

where \( \hat{\mu}_{M^*t} \) is an exogenous innovation to money growth. The interest rate rule is

\[
\hat{R}_t = \rho_R \hat{R}_{t-1} + (1 - \rho_R) \left[ \theta_{\pi} \log \hat{\pi}_t + \theta_{y_{gap}} (\hat{y}_t - \hat{y}_{flex,t}) + \theta_{\Delta y} (\hat{y}_t - \hat{y}_{t-1}) \right]
\]

The model looks quite complicated but it simplifies considerably when we turn off different frictions. In particular, if we turn off habit persistence (\( b = 0 \)), investment adjustment cost (\( \chi = 0 \)), variable capital utilization (\( \sigma_u = \infty \)) and money transaction cost (\( \eta(v) = 0 \)), the real-side equations collapse to well-known counterparts of the baseline RBC model.
Figure 1: Variance decomposition for the first slope shock
Figure 2: Impulse responses to the slope shock
Figure 3: Impulse responses to news shock with Sims' (2009) original VAR
Figure 4: Impulse responses of slope shock and news shock
Figure 5: Comparison of the slope shock and the news shock series
Figure 6: Impulse responses of long rate, expectations hypothesis and term premium to slope shock
Figure 7: Impulse response of long rate, expectations hypothesis and term premium to news shock.
Figure 8: Impulse responses to news shock in version 1 of the model
Figure 9: Impulse responses to news shock in version 2 of the model.
Figure 10: Impulse responses to news shock for version 3 of the model.