Journal of Financial Economics 146 (2022) 1016–1043

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

What moves treasury yields?[☆]

Emanuel Moench[a,b,c,1,*], Soroosh Soofi-Siavash[d,e]

[a] Deutsche Bundesbank, Research Centre, Frankfurt am Main 60431, Germany
[b] Goethe University Frankfurt, Frankfurt am Main 60323, Germany
[c] CEPR, United Kingdom
[d] Bank of Lithuania, Totorių 4, Vilnius 01103, Lithuania
[e] Vilnius University, Saulėtekio 9, Vilnius 10222, Lithuania

ARTICLE INFO

Article history:
Received 6 April 2021
Revised 1 April 2022
Accepted 3 April 2022
Available online 30 April 2022

JEL classification:
C55
E43
E44
G12

Keywords:
Term structure of interest rates
Yield curve
News shocks
Volatility shocks
Business cycle news
Structural dynamic factor models

ABSTRACT

We identify a yield news shock as an innovation that does not move Treasury yields contemporaneously but explains a maximum share of their future variation. Yields do not immediately respond to the news shock as the initial reaction of term premiums and expected short rates offset each other. While the impact on term premiums fades quickly, expected short rates and thus yields decline persistently. As a result, the shock explains a staggering 50% of Treasury yield variation several years out. A positive yield news shock is associated with a coincident sharp increase in stock and bond market volatility, a contemporaneous response of leading economic indicators, and is followed by a persistent decline of real activity and inflation which is accommodated by the Federal Reserve. Identified shocks to realized stock market volatility and business cycle news imply similar impulse responses and together capture the bulk of variation of the yield news shock.

1. Introduction

Government bonds play a benchmark role in financial markets and are therefore key to understanding the transmission of shocks in the economy. While much of the previous literature has studied the factor structure in government bond yields and the interaction of the term structure factors with macroeconomic aggregates, surprisingly little effort has been devoted to understanding the sources of yield curve variation. In this paper, we aim to fill this gap by identifying the shocks that move Treasury yields, and by studying the macroeconomic and financial market dynamics associated with these shocks.

The comovement among large panels of macroeconomic and financial time series has been shown to be well captured by a small number of factors (e.g.,

☆ Nikolai Roussanov was the editor for this article. We would also like to thank an anonymous referee, Jean-Sébastien Fontaine, André Kurmann (discussant), Sydney Ludvigson, Helmut Lütkepohl, Harald Uhlig and seminar participants at the Bank of Lithuania, the German Institute for Economic Research (DIW), Humboldt University Berlin, the San Francisco Fed/Bank of Canada Workshop on Advances in Fixed Income and Macro-Finance Research, the International Association for Applied Econometrics, the Baltic Economic Conference, the North American Summer Meeting of the Econometrics Society, the University of Birmingham and Vilnius University for helpful comments and discussions. The views expressed here do not reflect the views of the Bank of Lithuania or the Eurosystem. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

* Corresponding author at: Deutsche Bundesbank, Research Centre, Frankfurt am Main 60431, Germany.

E-mail address: e.moench@fs.de (E. Moench).

[1] Present address: Frankfurt School of Finance & Management, Adickesallee 32–34, 60322 Frankfurt am Main, Germany.

https://doi.org/10.1016/j.jfineco.2022.04.001

Sargent and Sims, 1977; Forni et al., 2000; Stock and Watson, 2002a,b). Similarly, the variation of government bond yields of different maturities is also known to be summarized by only a few factors (Garbade, 1996; Litterman and Scheinkman, 1991; Diebold and Li, 2006). We can therefore characterize the common dynamics of macroeconomic variables and Treasury yields in a dynamic factor model (DFM) where the macroeconomic and yield curve factors follow a joint vector autoregression. This allows us to identify the innovations driving yield curve variation, and to study the responses of a large number of macroeconomic and financial variables to these innovations in a unified framework. The bulk of the comovement among government bond yields is captured by the first two principal components, commonly referred to as level and slope. Innovations to the level factor result in parallel shifts and innovations to the slope factor in a flattening or steepening of the yield curve. Combined, they explain almost all of the short-term variation of yields. However, we show that these innovations together account for at most half of the variation of Treasury yields several years out.

What drives yield curve variation at these longer horizons? Recent studies have argued that there are factors which help to predict future bond yields but are not (well) spanned by the cross-section of contemporaneous yields. Cochrane and Piazzesi (2005) document that a linear combination of forward rates has strong forecasting power for bond returns but is only weakly correlated with yields contemporaneously. Ludvigson and Ng (2009) show that factors extracted from a large panel of macroeconomic and financial time series also predict bond returns well. Duffee (2011) uses Kalman filtering techniques to identify a linear combination of yields which has almost no immediate but a strong delayed impact on yields. Joslin et al. (2014) document that real economic growth and inflation contain predictive information about future bond yields over and above their first three principal components. Feunou and Fontaine (2018) show that a term stucture model with non-Markovian risk factors matches well the empirical observation that higher order yield principal components have incremental predictive power for future yields. Taken together, this evidence strongly suggests the existence of shocks which are orthogonal to the yield curve contemporaneously but which move bond yields with some delay.

Conceptually, such shocks would be similar to news shocks identified in the macroeconomic literature. Several authors have documented a delayed and persistent response of total factor productivity (TFP) to news shocks, see for example Beaudry and Portier (2006) and Barsky et al. (2015). Barsky and Sims (2011) identify a productivity news shock as the innovation orthogonal to current TFP that best explains variation in future TFP. Their identification strategy maximizes the forecast error variance (FEV) of TFP in a small-scale vector autoregression (VAR) subject to some orthogonality constraint. We use the same idea to identify a yield news shock which is hidden by contemporaneous Treasury yields but best explains their future variation. Specifically, we identify the innovation that jointly maximizes the equally-weighted forecast error variance shares of level and slope over the next year, but is orthogonal to the innovations which affect these two factors contemporaneously.[1]

Combined, the three shocks explain essentially all of the variation of yields. While the news shock does not move yields initially, it explains a staggering 50% of their variation at forecast horizons up to three years out. Consistent with the previous literature on hidden factors in the term structure, a positive yield news shock initially moves the expected future short rate and term premium components of Treasury yields in opposite directions. While the term premium response dies out relatively quickly, expected future short rates and with them yields continue to fall over subsequent years. A positive yield news shock is also associated with sharp increases in implied stock and bond market volatility, falling stock prices, and large contemporaneous responses of leading business cycle indicators, followed by a protracted decline of real activity and inflation. The Federal Reserve responds by persistently lowering the policy rate, which in turn feeds through to persistently lower expected future short rates and Treasury yields.

The sharp contemporaneous response of stock and bond market volatility to the identified yield news shock and the following decline of real activity suggest that broader financial market volatility may be a key driver of persistent yield curve variation. To verify this conjecture, we explicitly identify shocks that explain a maximum share of near-term variation in measures of implied and realized stock market volatility. We find a striking similarity of the impulse responses to these volatility shocks and the yield news shock, and show that they are highly correlated. In a recent paper, Berger et al. (2020) use a measure of realized stock market volatility along with the option-implied volatility index VXO to disentangle innovations to the realization of volatility from those to uncertainty about future stock prices. They document that it is innovations to realized rather than to expected future volatility that strongly affect macroeconomic aggregates. In line with their results we show that shocks to realized volatility and not those to forward-looking uncertainty drive persistent yield curve variation.

The yield news shock is also associated with a strong contemporaneous response of leading business cycle indicators. We identify a business cycle news shock as the innovation that explains a maximum share of the forecast error variances of leading indicators over the next year. This shock implies similar impulse responses as the yield news and realized volatility shocks, and has a persistent effect on expected short rates and yields despite having only a modest impact on inflation.

While the realized volatility and business cycle news shocks are positively correlated with one another and with the yield news shock, together they explain only about three quarters of its variance. To understand the residual

[1] While our identification of a yield news shock is in the tradition of the macroeconomic news shocks literature, other recent work (for example Altavilla et al., 2017; Gurkaynak et al., 2020) uses high-frequency Treasury yield data and event-study approaches to measure the news embedded in macroeconomic releases and studies their effect on financial markets and the macroeconomy.

source of Treasury yield variation, we identify a yield news shock that maximizes the forecast error variance of level and slope over the next year but is orthogonal to shocks to level, slope, realized volatility and business cycle news. Although this shock carries little residual information about financial market volatility and real activity, it explains economically and statistically significant shares of Treasury yield variation. We show that this residual yield news shock is associated with movements in international sovereign bond markets, suggesting that global bond yield dynamics also contribute to persistent Treasury yield variation.

Our analysis is related to various strands of the literature on the forecastability and the economic driving forces of government bond yields. The paper most closely related to ours is Kurmann and Otrok (2013). These authors identify a news shock to the *slope* of the term structure of interest rates and trace its impact on macroeconomic variables in a small-scale VAR. They find that news about the yield curve slope is positively correlated with news about future TFP. While the two analyzes are clearly related, there are a number of important differences. First, we identify a news shock which maximizes the forecast error variance of level *and* slope as opposed to only the term structure slope. Since the level factor represents by far the most important dimension of yield comovement, our yield news shock explains a much larger share of yield variation than the slope news shock of Kurmann and Otrok. The second key difference is that we can trace the impulse responses of a wide range of macroeconomic and financial time series in our DFM approach. This allows for a broad economic interpretation of the identified shocks. Our results imply that financial market volatility and news about the near-term economic outlook are more important drivers of yields than news about future productivity. In a robustness analysis, we identify a slope news shock à la Kurmann and Otrok (2013) and show that it has similar properties as the contemporaneous shock to the slope factor to which our yield news shock is orthogonal by construction.

Our finding that hightened financial market volatility is associated with a decline of expected short rates and an increase of term premiums is broadly consistent with several structural models of the term structure. Bianchi et al. (2019) propose a model with regime-switching uncertainty about aggregate demand and supply. They find that both types of uncertainty shocks lead to lower short rates and higher term premiums for longer-term bonds. Andreasen (2019) builds a model with autoregressive stochastic volatility which predicts an increase of term premiums in response to higher volatility. Amisano and Tristani (2019) propose a model with regime shifts in the conditional variance of productivity shocks. In their model, an increase in uncertainty raises term premiums and lowers expected real rates via a precautionary savings motive. In line with our findings, in these theories surprise innovations to volatility raise future uncertainty which leads to a drop in economic activity, lower short-term interest rates and higher term premiums. However, none of the aforementioned papers discusses the spanning (or, rather, the lack thereof) of shocks to volatility by contemporaneous yields, which is a key insight of our paper. Moreover, this literature also does not differentiate between contemporaneous shocks to volatility and independent shocks to expectations of future volatility, which we show to have very different effects on yields and other financial market indicators.

Our empirical results show a strong correlation of the yield news shock with a business cycle news shock. To the best of our knowledge, there is no structural model of the term structure of interest rates which incorporates such a shock. The closest equivalent to our business cycle news shocks in the macro literature is what Angeletos et al. (2018, 2020) refer to as *confidence* shocks. These shocks represent news about the near-term economic outlook which have little effect on longer-term output and on inflation but are a key driver of business cycles. In the model of Angeletos et al. (2018), a negative confidence shock leads to a temporary decline of wages and income which entails a weak wealth effect but a relatively strong substitution effect. Households respond by working less and by reducing both consumption and saving. Variation in confidence then generates positive co-movement between employment, output, consumption, and investment at the business-cycle frequency, similar to the effects of uncertainty shocks in the papers discussed above. As a result, negative news about the business cycle lead to persistently lower short rates, in line with our empirical results.

Our econometric approach builds on the literature that extends structural VAR methods to DFMs, see for example Forni et al. (2009), Forni and Gambetti (2010), and Stock and Watson (2016). Using a DFM, we consistently estimate the common and idiosyncratic components of a large number of variables. We then apply structural VAR methods to the innovations of the estimated factors to identify structural shocks based on a rich information set, and without the confounding influence of measurement errors and idiosyncratic variations.

The remainder of the paper is organized as follows. Section 2 presents our model and explains the identification of the yield news shock. Section 3 describes the data and details the estimation and model selection. Our empirical results, including several robustness analyzes, are documented in Section 4. Section 5 concludes.

2. Econometric methodology

In this section, we present our econometric methodology. We first describe the dynamic factor model which we use to summarize the joint dynamics of the Treasury yield curve and the U.S. macroeconomy. We then discuss our identification of shocks, which extends prior work on structural VARs following Uhlig (2003) to DFMs.

2.1. Model

We model the variation of a large number of macroeconomic and financial variables as well as Treasury yields using the DFM given by

$$X_t = \Lambda F_t + e_t, \tag{1}$$

for $t = 1, ..., T$, where X_t denotes the $N \times 1$ vector of observed time series, the factors in the $r \times 1$ vector F_t capture the common sources of variation among the variables X, Λ is the matrix of factor loadings, and e_t is a vector of idiosyncratic components. We further assume that the factors F_t follow a VAR:

$$\Phi(L)F_t = \eta_t, \tag{2}$$

where $\Phi(L) = I - \Phi_1 L - \cdots - \Phi_p L^p$ is a lag polynomial matrix, and η_t is the vector of factor innovations with mean zero and variance-covariance matrix Σ_η. From Eqs. (1) and (2), we obtain the reduced-form moving average representation which expresses X_t in terms of current and past values of innovations

$$X_t = \Lambda\Phi(L)^{-1}\eta_t + e_t. \tag{3}$$

Dynamic factor models of this form were first popularized by Stock and Watson (2002a,b) and have since become a workhorse tool to study the joint dynamics of large sets of macroeconomic and financial time series. Several authors (Joslin et al., 2014; Coroneo et al., 2016) have pointed out that macroeconomic factors that are not spanned by yields contemporaneously have strong forecasting power for future yields. To assess the importance of macroeconomic information in identifying shocks which move Treasury yields, we therefore estimate two specifications. One is an only-yields DFM with factors extracted exclusively from yields. Our baseline specification is a macro-yields model where we augment the yields with a large number of macroeconomic and financial variables and estimate a second set of factors driving these variables.

In DFMs, because the factors and their loadings are unobserved, the space spanned by the factors is identified, but the factors themselves are not ($\Lambda F_t = \Lambda G^{-1} G F_t$, where G is any invertible $r \times r$ matrix). Therefore, a normalization must be imposed. In our application of DFMs to the identification of a yield news shock, we use the following normalization

$$X_t = \begin{bmatrix} Y_t \\ Z_t \end{bmatrix} = \begin{bmatrix} \Lambda_{YY} & 0_{n\times(r-m)} \\ \Lambda_{ZY} & \Lambda_{ZZ} \end{bmatrix} \begin{bmatrix} F_t^Y \\ F_t^Z \end{bmatrix} + e_t. \tag{4}$$

Here, Y_t denotes the $n \times 1$ vector of Treasury yields with common dynamics captured by the $m \times 1$ vector of factors F_t^Y with loadings Λ_{YY}, and Z_t denotes the remaining macroeconomic and financial variables which are driven by F_t^Y and an additional set of factors F_t^Z with the corresponding loadings Λ_{ZY} and Λ_{ZZ}. This block-lower-triangular normalization has also been used in Coroneo et al. (2016). A key advantage of imposing this block-lower-triangular normalization on the factor loadings Λ in the macro-yields model is that the yield factors have the same interpretation across the two model specifications.

2.2. Identifying a yield news shock

We assume that the innovations η_t summarizing the joint dynamics among the variables in X_t are linear combinations of structural shocks, denoted by the $r \times 1$ vector ν_t:

$$\eta_t = H\nu_t. \tag{5}$$

The structural shocks ν_t have the variance-covariance matrix Σ_ν. Under the unit standard deviation normalization ($\Sigma_\nu = I$), one can write any matrix H as $H = Chol(\Sigma_\eta)Q$ where Q is a $r \times r$ orthonormal matrix ($Q'Q = I$), and $Chol$ denotes the Cholesky factorization. This implies the structural moving average representation

$$X_t = C(L)Q\nu_t + e_t, \text{ with } C(L) = \Lambda\Phi(L)^{-1}Chol(\Sigma_\eta), \tag{6}$$

where the impulse response function of X_t with respect to the ith shock is given by $C(L)Q_i$ with Q_i denoting the ith column of Q. Any potential mapping from the structural shocks ν_t to the innovations η_t can thus be captured by a choice of the matrix Q.

Under the normalization in Eq. (4), the moving average representation of the factor VAR is

$$F_t = \begin{bmatrix} F_t^Y \\ F_t^Z \end{bmatrix} = \begin{bmatrix} D_Y(L) \\ D_Z(L) \end{bmatrix} Q\nu_t = D(L)Q\nu_t, \tag{7}$$

where $D(L) = \Phi(L)^{-1}Chol(\Sigma_\eta)$, and the second expression partitions the lag polynomial similarly to F_t. Let D_k denote the kth lag matrix in $D(L)$ such that $D_{k,i}Q_j$ is the effect of the jth shock on the ith element of F_t after k periods.

In the application below, we seek to identify as few shocks as possible that summarize the common dynamics of Treasury yields. Let level and slope be the first two factors. We separate a yield news shock from contemporaneous shocks to level and slope by imposing the short-run timing restrictions:

$$\begin{bmatrix} \eta_t^{Level} \\ \eta_t^{Slope} \\ \eta_{3:rt} \end{bmatrix} = \begin{bmatrix} H_{11} & 0 & 0 \\ H_{21} & H_{22} & 0 \\ H_{\bullet 1} & H_{\bullet 2} & H_{\bullet\bullet} \end{bmatrix} \begin{bmatrix} \nu_t^{Level} \\ \nu_t^{Slope} \\ \nu_{3:rt} \end{bmatrix}, \tag{8}$$

where H_{11}, H_{21} and H_{22} are scalars. These restrictions deliver a recursive identification scheme which has also been used by other authors to identify shocks to yield curve factors, see for example Diebold et al. (2006) and Bianchi et al. (2009).

We seek to identify a yield news shock as the innovation which explains a maximum share of future variation of the yield curve level and slope, but does not move these two factors on impact. Letting the news shock be indexed by three, this is done by solving the following optimization problem

$$\underset{Q_3}{\operatorname{argmax}} \sum_{i=1}^{2} \frac{\sum_{k=0}^{h-1} \left(D_{k,i}Q_3\right)^2}{\operatorname{var}(F_{it+h}|F_t, F_{t-1}, \ldots)}, \tag{9}$$

subject to two constraints: (i) $Q_3'Q_3 = 1$, (ii) $H_{ij} = 0$, for $i = 1, \ldots, 2$ and $j = 3, \ldots, r$. The first constraint ensures that Q_3 is an orthonormal vector. The second constraint imposes the restrictions (8) on the matrix H so that the third shock does not affect the first two factors within the same period. The solution to this problem is characterized by an eigenvector associated with the first eigenvalue of the lower $(r-2) \times (r-2)$ block of the matrix $\sum_{k=0}^{h-1}\left(D_{k,1:2}' S_{2\times 2} D_{k,1:2}\right)$, where $D_{k,1:2}$ denotes the first two rows of D_k, and $S_{2\times 2}$ is a diagonal matrix with entries $\operatorname{var}\left(F_{it+h}|F_t, F_{t-1}, \ldots\right)^{-1}$ for $i = 1, 2$. In our empirical analysis, we set $h = 12$ and thus maximize the explanatory power of the yield news shock for future yields at the one year horizon.

Our approach to identify a yield news shock as the innovation which explains the maximum share of variation of Treasury yields Y_t follows Uhlig (2003) who originally proposed a similar shock identification strategy in the context of structural VARs. The method has also been applied to identify news shocks about future TFP (Barsky and Sims, 2011; Forni et al., 2014), shocks to the yield curve slope (Kurmann and Otrok, 2013), and technology shocks (Francis et al., 2014), among others. Our approach translates the notion of "hidden" (Duffee, 2011) or "unspanned" (Joslin et al., 2014) factors in the term structure of interest rates into a shock rather than a factor identification strategy.

3. Empirical implementation

In this section, we first describe the data used in our empirical analysis, then summarize the individual steps to obtain estimates and standard errors, and discuss model selection.

3.1. Data

Our data are monthly and cover the sample period from July 1962 to June 2019. We summarize the Treasury yield curve using 109 yields on zero-coupon Treasuries with maturities from 12 to 120 months. We obtain these as end-of-month observations from Gurkaynak et al. (2007). We further include the expected average future short rate and term premium components for the yields with maturities 24, 60 and 120 months based on the model by Adrian et al. (2013, henceforth ACM).

In the macro-yields specification, we augment these yields and yield components with a large set of macroeconomic and financial time series covering the most important categories of U.S. economic activity. We obtain these from the FRED-MD database compiled by McCracken and Ng (2016). We further include average weekly hours of production and non-supervisory employees; the Philadelphia Fed leading indicator for the U.S. economy; the VXO index which measures volatility implied in S&P100 options; the measure of realized stock market volatility from Berger et al. (2020) extended to the end of our sample (RVol); the Bank of America Merrill Lynch MOVE bond volatility index, which captures implied volatility from a basket of Treasury options; a measure of financial uncertainty from Ludvigson et al. (2021, henceforth LMN); the excess bond premium from Gilchrist and Zakrajšek (2012, henceforth GZ); and the three-Month Treasury bill forecast from the Consensus Economics Survey of Professional Forecasters. Of the 135 series, 125 are available from July 1962 to June 2019. A complete list of macroeconomic and financial variables is provided in the Online Appendix.

3.2. Estimation and standard errors

We estimate the model using a two-step approach. First, we estimate the yield curve factors F_t^Y as principal components of the set of 109 Treasury yields. For the macro-yields model, we augment the estimates of F_t^Y with macroeconomic factors. We normalize these to be unconditionally orthogonal to the yield curve factors by regressing the macroeconomic variables on the estimate of F_t^Y, and then computing principal components of the residuals. This estimation procedure resembles that of FAVARs as described by Stock and Watson (2016), where the estimates of F_t^Y are treated as observed. It ensures that the yield factor loadings Λ_{YY} are identical in both models and that the first two yield principal components have the interpretation as level and slope in both specifications. As a second step, given the estimated set of factors, we estimate factor VARs with the lag order selected by BIC with $1 \leq p \leq 12$.

To compute standard errors for the impulse response functions and forecast error variance decompositions, we use a parametric bootstrap following Stock and Watson (2016), which proceeds with the following steps: (1) Estimate Λ, F_t, $\Phi(L)$, Σ_η and the idiosyncratic vector of residuals $\hat{e}_t = X_t - \hat{\Lambda}\hat{F}_t$; (2) Estimate univariate ARs for idiosyncratic residuals, $\hat{e}_{it} = \alpha_i(L)\hat{e}_{it-1} + u_{it}$; (3) Generate random draws $\tilde{\eta}_t \overset{iid}{\sim} N(0, \hat{\Sigma}_\eta)$ and $\tilde{u}_{it} \overset{iid}{\sim} N(0, \hat{\sigma}_i^2)$ and use them to generate bootstrap data as $\tilde{X}_t = \hat{\Lambda}\tilde{F}_t + \tilde{e}_t$ with $\hat{\Phi}(L)\tilde{F}_t = \tilde{\eta}_t$ and $\tilde{e}_{it} = \hat{\alpha}_i(L)\tilde{e}_{it} + \tilde{u}_{it}$; (4) Estimate the model parameters, impulse response functions and forecast error variance decompositions; (5) Repeat steps (3)-(4) for 500 bootstrap replications and compute the standard errors.

3.3. Model selection

Stock and Watson (2002a) show that the space spanned by the factors can be constructed by principal components analysis when N and T are large and the number of principal components is equal to or greater than the number of factors r. The number of factors can be consistently estimated when N and T are large using the criteria from Bai and Ng (2002). These balance the benefit of adding a factor against the cost of increased sampling variability.

Crump and Gospodinov (2022) note that estimation of the true number of yield curve factors may be empirically problematic for two reasons. First, since yields are highly persistent time series, estimates of the number of factors could be overstated. Second, the fact that yields represent cross-sectional averages of one-period forward rates could lead to a spuriously small estimated number of factors. We estimate the number of factors driving yields ($N = 109$) and the remaining macroeconomic data ($N = 135$) using Bai-Ng (2002) IC2, and in light of the analysis in Crump and Gospodinov (2022) consider the predictive ability for future yields as an additional criterion.

Table 1 provides the Bai-Ng (2002) IC2 criterion for yields and macroeconomic variables for a given number of factors i, along with the trace R^2 that measures the fraction of total variance explained by the factors 1 to i, and the marginal trace R^2 of factor i. For the macroeconomic dataset, the trace R^2 of the first factor is much smaller (about 0.15) and the contributions of higher-order factors decline slowly compared to the yield dataset. The Bai-Ng (2002) IC2 selects eight factors which capture more than 48% of the variation of all FRED-MD series. This estimate is consistent with McCracken and Ng (2016), who also estimate eight factors for essentially the same

Table 1
Statistics for estimating the number of factors. The trace R^2 values capture the fraction of total variation explained in the data by the row number of factors. The Bai-Ng (2002) IC2 criterion balances the benefit of adding an additional factor against the cost of increased sampling variability in static factor models.

(a) Yield dataset ($N = 109$)			
Number of static factors	Trace R^2	Marginal trace R^2	Bai-Ng (2002) IC2
1	0.99	0.99	-4.50
2	1.00	0.01	-7.60
3	1.00	0.00	-10.47
4	1.00	0.00	-13.00
5	1.00	0.00	-15.52
(b) Macroeconomic dataset ($N = 135$)			
Number of static factors	Trace R^2	Marginal trace R^2	Bai-Ng (2002) IC2
1	0.15	0.15	-0.12
2	0.22	0.07	-0.16
3	0.29	0.07	-0.21
4	0.35	0.06	-0.25
5	0.39	0.04	-0.27
6	0.43	0.04	-0.28
7	0.46	0.03	-0.29
8	0.48	0.02	-0.29
9	0.50	0.02	-0.29
10	0.52	0.02	-0.28

set of variables and a slightly shorter sample. For the yield dataset, the trace R^2 shows that the first factor explains around 99% of the overall variance of yields in our sample, in line with previous evidence. Despite this large share of variance explained by the first principal component, the Bai-Ng (2002) IC2 criterion selects five yield factors (the maximum number of factors we consider).

While the higher-order yield curve factors have tiny marginal explanatory power for yield variances, they have significant marginal predictive power for future individual yields, as we show next. Specifically, we run the following regressions of one-year yield changes on factor estimates, $\hat{F}_t$:

$$y^{(n)}_{t+12} - y^{(n)}_t = \beta_0 + \beta_1' \hat{F}_t + e_{t+12}, \tag{10}$$

where e_{t+12} are innovations orthogonal to $\hat{F}_t$. Table 2 reports the estimates of β_1, and the $\bar{R}^2$ for the two, five, and ten-year Treasury, assuming different numbers of yield curve factors. We compute Newey-West HAC standard errors with 18 lags, following Cochrane and Piazzesi (2005). For all three maturities the fifth yield curve principal component, $\hat{F}_{5t}$, has strongly significant marginal predictive power for future yield changes. Including the fourth and fifth yield curve principal components (columns 2, 5, and 8) markedly increases predictability with respect to the first three principal components (columns 1, 4, 7), with the $\bar{R}^2$ increasing from 5 to 9% for the two-year maturity, from 8 to 13% for the five-year maturity, and from 14 to 19% for the ten-year maturity. Adding the eight additional macro factors (columns 3, 6, 9) further raises predictability, with $\bar{R}^2$ values increasing to 22–25%. This is consistent with e.g. Moench (2008) and Ludvigson and Ng (2009) and suggests that information embedded in these macro factors helps to capture future yield variation.

Informed by these results, we set the number of yield factors to five in both specifications. This choice is consistent with ACM, who use the same underlying Treasury yield data but a different sample and test for the number of factors using a rank test of the factor loading matrix. Another reason to include additional yield factors beyond the first three principal components is the "excess volatility" of asset prices relative to affine models. As Giglio and Kelly (2018) document, the volatility of very long-term Treasury yields exceeds that implied by a standard affine model with three factors. In unreported results, we find that a five-factor model for Treasuries does not exhibit excess volatility in our sample. Based on the BIC with $1 \leq p \leq 12$, we further set the lag order in the factor VARs to $p = 2$.[2]

4. Results

This section summarizes our results. We start by discussing the properties of the three identified shocks to the yield curve in Section 4.1. In Section 4.2, we identify innovations to realized and implied stock market volatility and document that these are strongly correlated with the yield news shock. Section 4.3 isolates shocks to contemporaneous volatility from those to expectations of future volatility. To shed further light on the link between yield news and leading economic indicators, we explicitly identify a business cycle news shock in Section 4.4 and study the variation of yield news unexplained by realized volatility and business cycle news in Section 4.5. Section 4.6 performs several robustness analyzes.

4.1. Yield curve shocks

We start by documenting that the three yield curve shocks combined explain all yield curve variation.

[2] The estimated lag order greater than one in the only-yields model is consistent with recent evidence that yield dynamics may not be fully Markovian; see e.g. Cochrane and Piazzesi (2005) and Hanson et al. (2021).

Table 2
OLS regressions of one-year change in Treasury yields on lagged factors. $\hat{F}_1^{Level}$, $\hat{F}_2^{Slope}$, $\hat{F}_3^{Curv.}$, $\hat{F}_4^{Y}$ and $\hat{F}_5^{Y}$ denote the yield curve level, slope, curvature and 4th and 5th yield factors, all estimated by principal components using yields with maturities from 12 to 120 months. $\hat{F}_1^{Z}, \hat{F}_2^{Z},..., \hat{F}_8^{Z}$ denote eight macroeconomic factors estimated by first regressing 135 FRED-MD series on the five yield curve factors and then extracting principal components from the residuals. The numbers in parentheses are standard errors computed by Newey-West HAC with 18 lags. The factor estimates are normalized to have unit standard deviation. Coefficients that are statistically significant at the 10% level are highlighted in bold. A constant is always included in the regression even though its estimate is not reported in the table.

Model: $y_{t+12}^{(n)} - y_t^{(n)} = \beta_0 + \beta_1'\hat{F}_t + e_{t+12}$									
	$y_{t+12}^{(2)} - y_t^{(2)}$			$y_{t+12}^{(5)} - y_t^{(5)}$			$y_{t+12}^{(10)} - y_t^{(10)}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\hat{F}_t^{Level}$	**-0.32**	**-0.32**	**-0.31**	-0.22	-0.22	-0.21	-0.14	-0.14	-0.14
	(0.19)	(0.18)	(0.16)	(0.16)	(0.15)	(0.13)	(0.14)	(0.14)	(0.12)
$\hat{F}_t^{Slope}$	-0.07	-0.06	-0.06	**-0.25**	**-0.25**	**-0.24**	**-0.36**	**-0.36**	**-0.35**
	(0.14)	(0.14)	(0.14)	(0.12)	(0.12)	(0.12)	(0.10)	(0.10)	(0.10)
$\hat{F}_t^{Curv.}$	0.00	0.00	0.01	0.14	0.14	0.14	0.12	0.13	0.13
	(0.15)	(0.14)	(0.13)	(0.12)	(0.12)	(0.11)	(0.10)	(0.10)	(0.10)
$\hat{F}_{4t}^{Y}$		-0.04	-0.04		-0.05	-0.06		-0.09	-0.09
		(0.10)	(0.08)		(0.08)	(0.07)		(0.07)	(0.06)
$\hat{F}_{5t}^{Y}$		**0.32**	**0.32**		**0.26**	**0.27**		**0.22**	**0.22**
		(0.11)	(0.12)		(0.08)	(0.09)		(0.07)	(0.08)
$\hat{F}_{1t}^{Z}$			**-0.34**			**-0.18**			-0.09
			(0.12)			(0.09)			(0.08)
$\hat{F}_{2t}^{Z}$			**0.05**			**0.04**			**0.04**
			(0.03)			(0.02)			(0.02)
$\hat{F}_{3t}^{Z}$			**0.27**			**0.19**			**0.14**
			(0.09)			(0.07)			(0.05)
$\hat{F}_{4t}^{Z}$			**-0.25**			**-0.17**			-0.11
			(0.09)			(0.07)			(0.07)
$\hat{F}_{5t}^{Z}$			0.03			-0.03			-0.08
			(0.10)			(0.08)			(0.06)
$\hat{F}_{6t}^{Z}$			**0.13**			**0.13**			**0.13**
			(0.06)			(0.05)			(0.04)
$\hat{F}_{7t}^{Z}$			-0.03			-0.02			-0.03
			(0.04)			(0.04)			(0.03)
$\hat{F}_{8t}^{Z}$			-0.10			-0.08			**-0.07**
			(0.06)			(0.05)			(0.04)
$\bar{R}^2$	0.05	0.09	0.22	0.08	0.13	0.22	0.14	0.19	0.25

Fig. 1 (panel a) provides forecast error variance decompositions for the two-year (top row), five-year (middle row), and ten-year Treasury yields (bottom row). The first three columns provide the shares of FEV explained by the level, slope and yield news shocks, and the last column provides the sum of the shares explained by the three shocks. The blue dashed lines show the estimates from the only-yields, the black solid lines from the macro-yields model. In both specifications, the level shock explains at least 90% of the contemporaneous response of Treasury yields. The contribution of this shock to the FEV declines to about 70% at the three-year horizon in the only-yields model, and to about 50% in the macro-yields model. A shock to the slope factor explains considerably smaller shares of variance; it is highest at about 15% of the variance on impact for the two-year maturity, and slowly declines towards zero for longer forecast horizons. The variance shares explained by the slope shock are similarly low in both the only-yields and the macro-yields specifications.

The FEV contributions of the yield news shock, shown in the third column, are strikingly different. As imposed through its orthogonality with level and slope, the news shock explains essentially none of the contemporaneous variation of yields. However, the longer the forecast horizon the more prominent the role of the yield news shock. At the three-year horizon, the shock explains about 30% of the yield curve variation in the only-yields and a staggering 50% in the macro-yields model.[3] Hence, a large share of the medium to longer-term variation in Treasury yields is driven by a shock that does not move yields contemporaneously. This finding strongly supports previous evidence for unspanned or hidden factors in the term structure of interest rates. The fact that the FEV contributions of the news shock are substantially larger in the macro-yields model further suggests that macroeconomic information that is not captured by yields contemporaneously explains future yield curve variation.

Strikingly, the three shocks combined explain essentially all of the variation in Treasury yields for horizons as far as three years out. In other words, the dynamic rank of the Treasury yield curve is three. Hence, studying these three shocks we can disentangle the different driving forces of Treasury yields. The bottom panel of Fig. 1 shows that the level and slope shocks identified in the two

[3] Note that these estimates are from two structural DFMs with a different number of factors (5 in the only-yields and 13 in the macro-yields model), and therefore one may view them as not being fully comparable. As an alternative, we have applied the Gorodnichenko and Lee (2020) R^2 method for consistent comparison of the contributions of the identified shocks from different model specifications. The results are essentially identical to those in Fig. 1, and thus support the comparison of estimates across our two different structural DFM specifications.

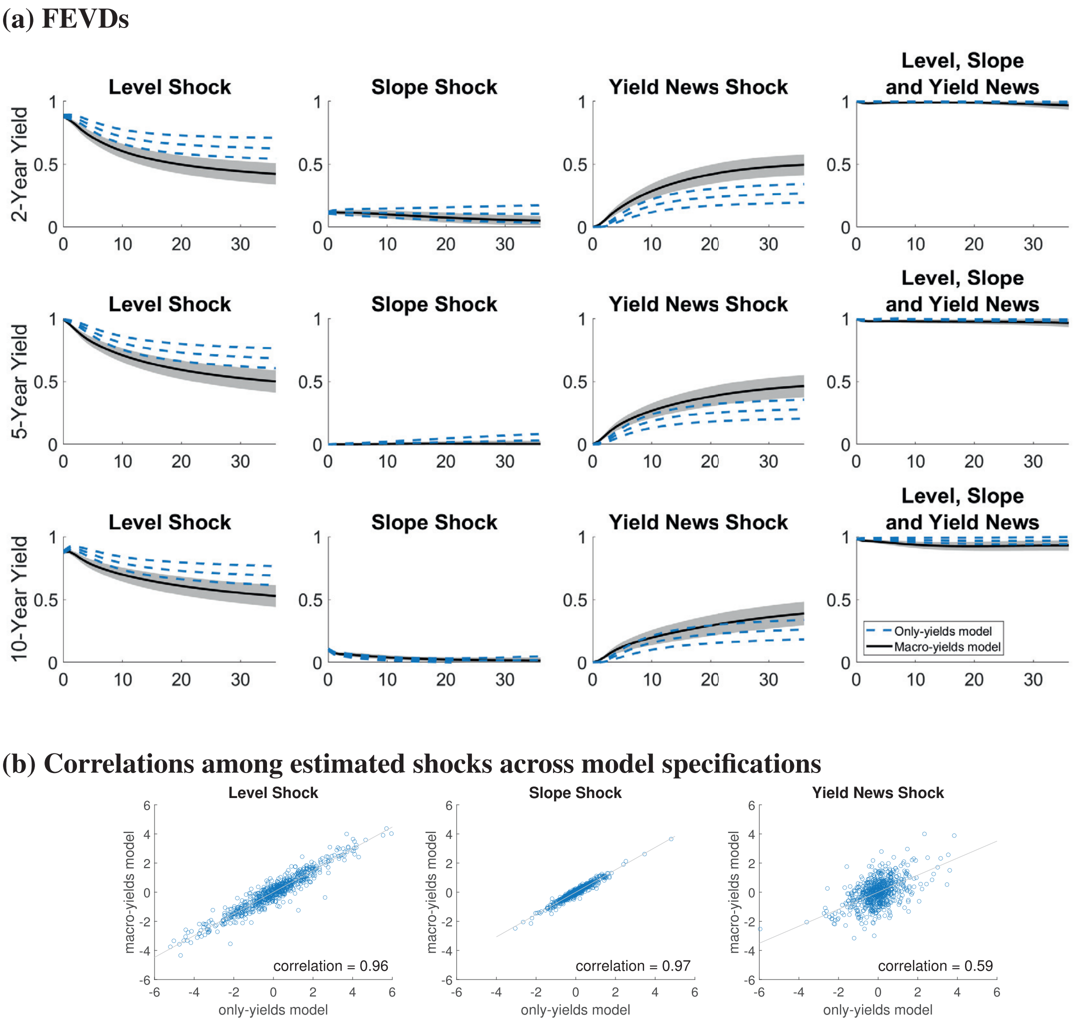


Fig. 1. FEVDs from only-yields and macro-yields DFMs. The top panel of this figure shows the FEVDs from the only-yields model (blue dashed ±1 standard error bands), and the macro-yields model (black solid ±1 standard error bands) for the level, slope and yield news shocks, as well as the three shocks combined. The bottom panel provides scatter plots of each shock estimated in the two model specifications.

model specifications are almost perfectly correlated, while the correlation between the yield news shocks across the two models is about 60%. This reinforces the notion that macroeconomic information is important for future yield curve variation, over and above the information contained in yields themselves. In the following, we therefore focus on the shocks identified in the richer macro-yields model.[4]

Yield response to yield curve shocks Our identification of shocks driving Treasury yields follows statistical criteria. We provide an economic interpretation of the shocks via impulse response analysis. We show the impulse responses of the two- and ten-year Treasury yields to the shocks in the first column of Fig. 2. We scale all three shocks so that they each lead to the same peak decline of the two-year yield of about 25 basis points as implied by a one-standard-deviation impulse of the yield news shock.

The level shock, shown in the top row, reduces both yields by about 23 and 17 basis points on impact. The responses are quite persistent with a half-life of about two years. The slope shock (middle row) implies initial responses of opposite sign for the two-year and the ten-year Treasury. While the two-year Treasury falls by about 20 bps, the ten-year yield increases by a similar amount, thus resulting in a steepening of the yield curve by almost 50 bps. Slope shocks are less persistent than level shocks, and die out after about 18 months. In contrast, the yield news shock (bottom row) does not move yields on impact, as per construction. However, yields drop sharply during the first few months after the shock hits, with the two-year yield declining by 25 bps and the ten-year yield by about 15 bps after one year. The responses are even

[4] Note that we use final revised macroeconomic data in our analysis. Ghysels et al. (2018) show that the predictive content of macro variables for future bond returns is considerably higher when final revised instead of real-time data are considered. Moreover, macroeconomic data revisions are correlated with future bond yields. Some of the additional predictive content of news shocks in the macro-yields model might thus be attributed to embedded data revision components.

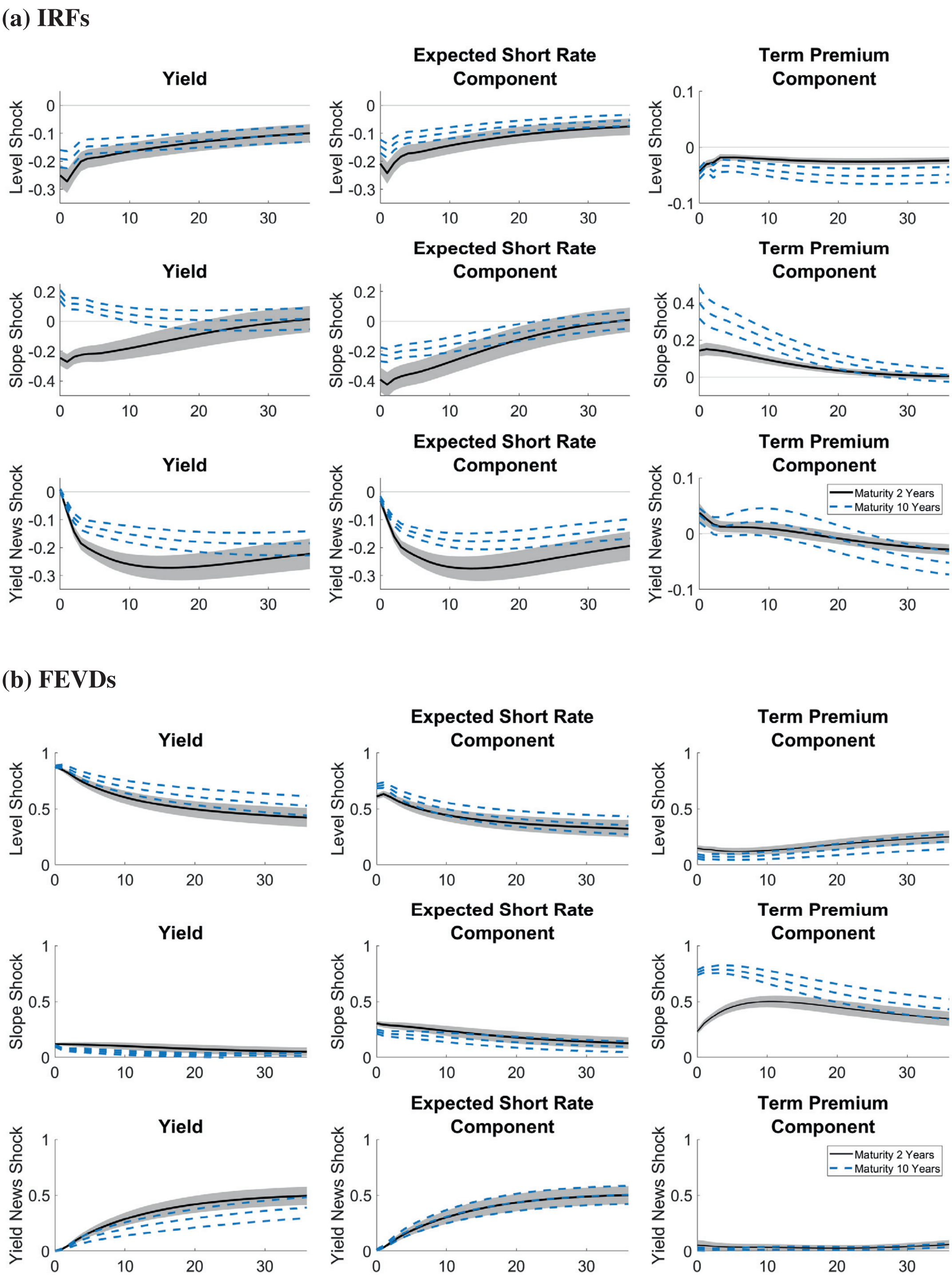


Fig. 2. IRFs and FEVDs of yields and their components to yield shocks. The top panel of this figure shows the IRFs for the level, slope and yield news shocks for yields and their expected short rate and term premium components for the two-year (black solid ±1 standard error bands) and the ten-year (blue dashed ±1 standard error bands) maturity from the macro-yields model. The yield news shock is reported as a one-standard deviation impulse, and the responses for level and slope shocks are scaled so that they each produce the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

more persistent than those of the level shock, and remain substantially negative in the first three years.

How can a shock that does not move yields contemporaneously have such a strong effect on future yields? A common explanation in the literature on unspanned factors in the term structure is that such factors have an offsetting initial impact on the term premium and expected short rate components of yields, but differential impacts at longer horizons. We check if this is also the case for the yield news shock by studying its impact on both yield components which we obtain from ACM.[5] As we use the same underlying yields in our analysis and as the ACM model fits these yields close to perfectly, the impulse responses of the expected short rate and term premium components sum to the responses for the corresponding yield itself.

The top panel of Fig. 2 provides the impulse responses. The first column shows the response of yields, the middle that of expected short rates and the last column that of term premiums. Focusing on the level shock first (top row), we see that the bulk of the yield response to that shock is driven by a sharp and persistent drop of expected future short rates, accompanied by a quantitatively smaller but also persistent decline in term premiums. The slope shock (middle row) elicits an initial reduction of expected future short rates of about 40 bps at the two-year maturity and 20 bps at the ten-year maturity. The decline in expected short rates is relatively persistent, taking two years to converge back to zero. Interestingly, the slope shock is also followed by a persistent increase in term premiums, which partly offsets the initial decline in expected short rates. The responses to the yield news shock (bottom row) show that expected future short rates drop by only a few basis points initially, but then continue to decline sharply over the next year or so, largely mimicking the shape and magnitude of the yield responses. Term premiums initially rise by the same amount as risk-neutral yields fall. As a result, the on-impact response of yields – which equals the sum of the two components – is essentially zero, thus “hiding” the news shock in contemporaneous yields. Notably, while the yield news shock initially drives up term premiums by a few basis points, that response turns negative after about two to three years, thus contributing to the strong and persistent response of yields to the news shock at longer horizons.

The initial increase of the term premium is explained by a decline in the price of level risk in response to the yield news shock. As shown in ACM, variation in the price of level risk is primarily driven by the fifth principal component of Treasury yields, consistent with the strong predictive power of this factor for future yield changes that we have documented above. In unreported results, we confirm that this factor sharply declines in response to a positive yield news shock, pushing down the price of level risk. As in ACM, we ensure that yields of all maturities load positively on the level factor. Since bond returns are scaled negative yield changes, the betas on excess returns and thus term premiums are negative multiples of the yield loadings. Hence, a decline in the price of level risk raises the term premium.

The bottom panel of Fig. 2 shows the FEV decompositions for the yields and their two components. The charts highlight that yield variation at shorter horizons in response to the level shock (top row) is almost entirely driven by the response of expected future short rates and only to a small extent by term premiums. The opposite picture emerges for the slope shock (middle row). It explains about 20–30% of the variation of expected short rates on impact, and this fraction slowly declines with the forecast horizon. In contrast, the slope shock accounts for about 80% of the variation of the ten-year term premium on impact, which declines to a sizable 50% after three years. It is worth noting that since the expected short rate and term premium responses to the slope shock are of opposite signs, the sizable term premium variance shares explained by the slope shock do not translate into substantial yield variation. Turning to the bottom row, we see that essentially all of the yield variation induced by the news shock is driven by its highly persistent impact on expected future short rates. Only small fractions of term premium variation are explained by the news shock. At longer horizons, yield variation is accounted for by level and news shocks in similar magnitudes, and is mainly driven by the expected short rate component. To better understand the economics behind the three shocks driving Treasury yields, we next study their impact on key financial and macroeconomic variables.

Financial market response to yield curve shocks The top panel of Fig. 3 provides impulse responses of the S&P500 index, MOVE, VXO, RVol, and the EBP. For comparison, we again show the responses of the two-year Treasury yield. Focusing first on the S&P 500, we see that stock prices rise by about 70 bps and remain elevated in response to a level shock (blue line), and drop by about 40 bps before they revert back to zero in response to a slope shock (black line). The S&P 500 drops much more strongly, by about 2%, in reaction to the yield news shock (red line), and this response is very long-lasting. Notice that the sharp decline of stock prices on impact is in stark contrast to the zero contemporaneous response of Treasury yields to a news shock.

Looking at the responses of VXO, RVol, MOVE and EBP, the following picture emerges. Level shocks have essentially no impact on any of these indicators. Slope shocks elicit a sizable response of Treasury option implied volatility, but only moderate responses of the other financial indicators. Again in sharp contrast, the yield news shock is associated with sharp and persistent increases of bond and stock market volatility. The VXO jumps by about 2.5% on impact, and only reverts back to its initial level after more than one year. This pattern is essentially mimicked by realized stock market volatility. The MOVE and the EBP all show similar responses. Hence, despite the fact that it is not apparent in Treasury yields initially, the yield

[5] Daily updates of these components can be found on Bloomberg and Haver, and also here: https://www.newyorkfed.org/medialibrary/media/research/data_indicators/ACMTermPremium.xls. Here, we use the end-of-month observations. Also note that the structural DFM estimate of the impulse response functions contain two parts: the loadings $\hat{\Lambda}$, and the moving average coefficients from the factor VAR, $\hat{D}(L)\hat{Q}$. We estimate the loadings for the components by regressing them on the model factors, but do not include the components in the vector of variables from which we extract the factors.

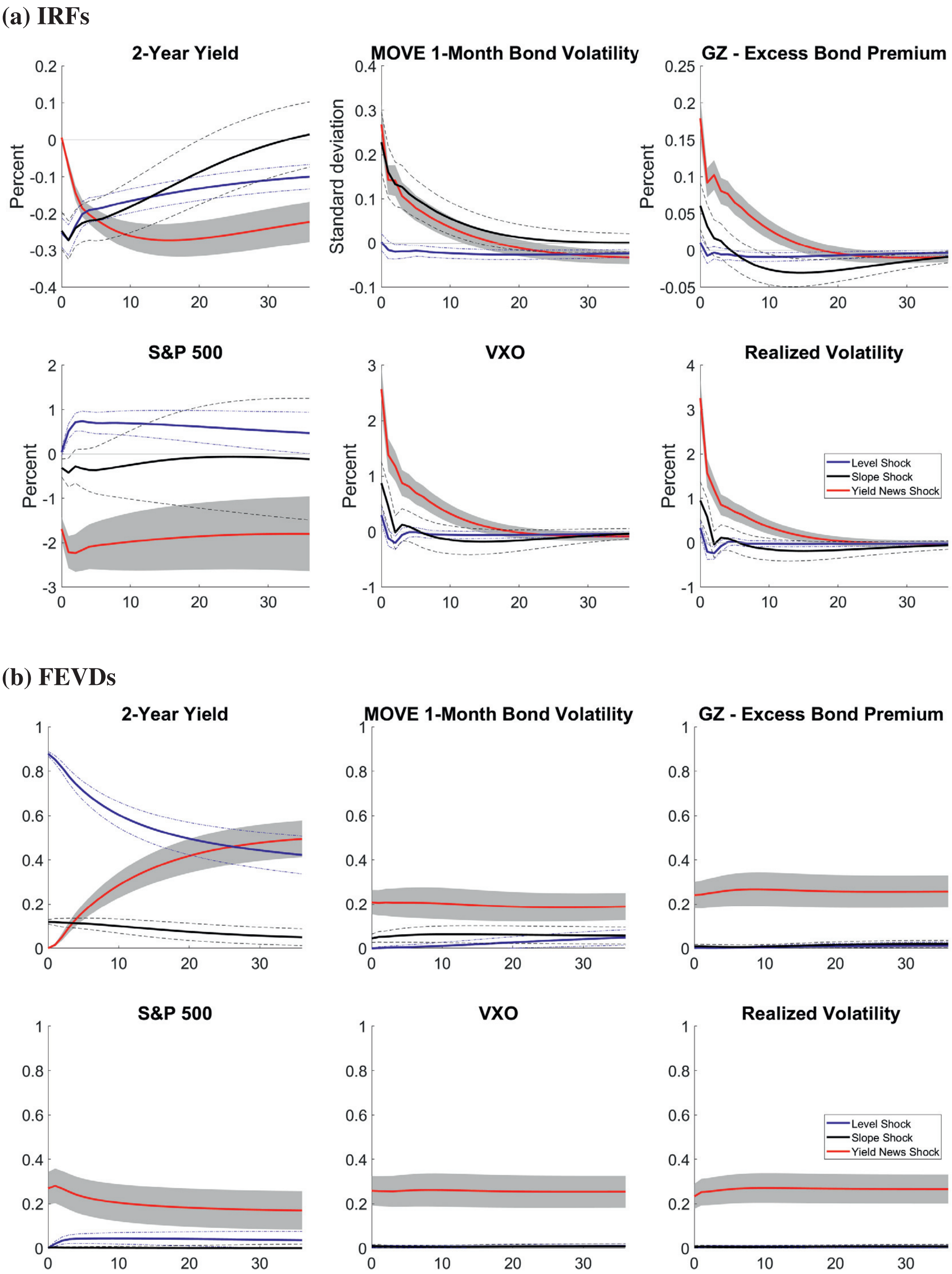


Fig. 3. IRFs and FEVDs of financial market indicators to yield shocks. The top panel of this figure shows the IRFs for the level shock (blue solid ±1 standard error bands), the slope shock (black solid ±1 standard error bands), and the yield news shock (red solid ±1 standard error bands) from the macro-yields model. The yield news shock is reported as a one-standard-deviation impulse, and the responses for the level and slope shocks are scaled so that they each produce the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

news shock is associated with large spikes in volatility and risk premium measures. This is also reflected in the FEV decompositions provided in the bottom panel of Fig. 3. The yield news shock accounts for around 20–30% of the forecast error variance of stock prices, financial volatility indices and the excess bond premium across forecast horizons. In contrast, the level and slope shocks explain little if any of the variation of these key financial market indicators.

Macroeconomic response to yield curve shocks A vast literature pioneered by Bloom (2009) has shown that shocks to implied and realized financial market volatility are important drivers of macroeconomic dynamics. Given that our identified yield news shock is associated with a sharp contemporaneous increase in realized and implied volatility, we next investigate its effects on macroeconomic aggregates.

The top panel of Fig. 4 provides impulse responses for key macro indicators to the three yield curve shocks. They show that contemporaneous innovations of the yield curve level have essentially no discernible effect on real macroeconomic aggregates. That said, they are associated with a small but persistent drop of CPI inflation and a persistent but shallow decline in the federal funds rate and in expected Treasury bill forecasts. The responses to the slope shock are more sizable. Industrial production, nonfarm payroll and personal consumption expenditures all start to rise after a few months and remain elevated, with industrial production increasing by about one percent after three years. This economic expansion is mirrored by a hump-shaped increase in the Philadelphia Fed leading indicator and housing starts, as well as a persistent decline of initial claims for unemployment insurance. The strong growth is supported by accommodative monetary policy as indicated by a lower federal funds rate and a lower expected path of policy rates.

The impulse responses associated with the yield news shock paint a different picture. All measures of real economic activity fall persistently. IP declines by a little less than one percent after one year, nonfarm payrolls fall by about half a percent, and personal consumption expenditures by about 0.2%. While the initial response of these measures of real activity is muted, the yield news shock is associated with a sharp on-impact response of several leading business cycle indicators, as shown in the second row of Fig. 4. The Philadelphia Fed leading indicator, housing starts, and initial claims all display a strong and persistent reaction when the yield news shock hits. Hence, in addition to hightened financial market volatility a positive realization of the yield news shock is associated with negative news about the state of the business cycle. The strong response of leading indicators is accompanied by a small but persistent drop in inflation. The Federal Reserve accommodates the decline of inflation and real activity by lowering the federal funds rate persistently. Professional forecasters understand this and also persistently lower their expectations of the three-month Treasury bill rate.

The forecast error variance decompositions in the bottom panel of Fig. 4 underscore these findings. The contributions of the level and slope shocks to the variation in key macroeconomic variables are small. The level shock only meaningfully contributes to the variation in the federal funds rate itself and expected future TBill yields. The slope shock explains some variation of real economic growth, especially at longer forecast horizons, consistent with a prior literature documenting predictive power of the term spread for economic conditions several quarters out. In sharp contrast, the yield news shock explains large fractions of the forecast error variance of macroeconomic aggregates at all but the shortest horizons. At the one-year horizon, the shock captures more than 40% of the variation of IP and a staggering 60% of the variation in nonfarm payrolls.

The top panel of Fig. 5 provides a time series plot of the identified yield news shock series. While the shock appears somewhat heavy-tailed, it does not feature much skewness. To better visualize its cyclical properties, the bottom panel of the figure shows the shock run through an AR(1) filter with autoregressive coefficient of 0.9. This chart indicates that recessions are associated with strings of positive yield news, while negative realizations tend to cluster right after recessions. The filtered series is strongly negatively correlated with 12-month IP growth, confirming the counter-cyclical behavior of the yield news shock series.

Combined with the impulse responses discussed above, this countercyclical pattern suggests that the yield news shock, which affects Treasury yields not contemporaneously but in the future, has properties akin to those documented for uncertainty shocks (e.g., Bloom, 2009; Basu and Bundick, 2017) and, more recently, shocks to realized stock market volatility as in Berger et al. (2020). In the next section, we explicitly contrast the impulse responses to the yield news shock with those to identified shocks to implied and realized stock market volatility.

4.2. Shocks to implied and realized stock market volatility

We follow Caldara et al. (2016) who use a structural VAR to identify an uncertainty shock as an innovation that leads to the largest positive response in a measure of uncertainty over the first six months after the shock hits. We deviate from their approach in two ways. First, we achieve identification by maximizing the forecast error variance share of an uncertainty measure in the same way as we identify the yield news shock. In contrast, Caldara et al. (2016) use a penalty function approach which maximizes the impulse responses as opposed to the forecast error variance of the target variable. Second, we identify the shock within our structural macro-yields DFM as opposed to a structural VAR. This allows us to estimate responses for the same variables in an internally consistent way and enables comparison of the responses to the yield news and uncertainty shocks. As our baseline measure, we use the VXO to identify an implied volatility shock. For comparison, we also show the responses for two more shocks targeting the MOVE and the LMN indices in Figs. A.1 to A.3 in the Online Appendix.

Measures of implied volatility from stock options are highly correlated with measures of realized stock market volatility. Berger et al. (2020) document that it is realizations of contemporaneous volatility rather than

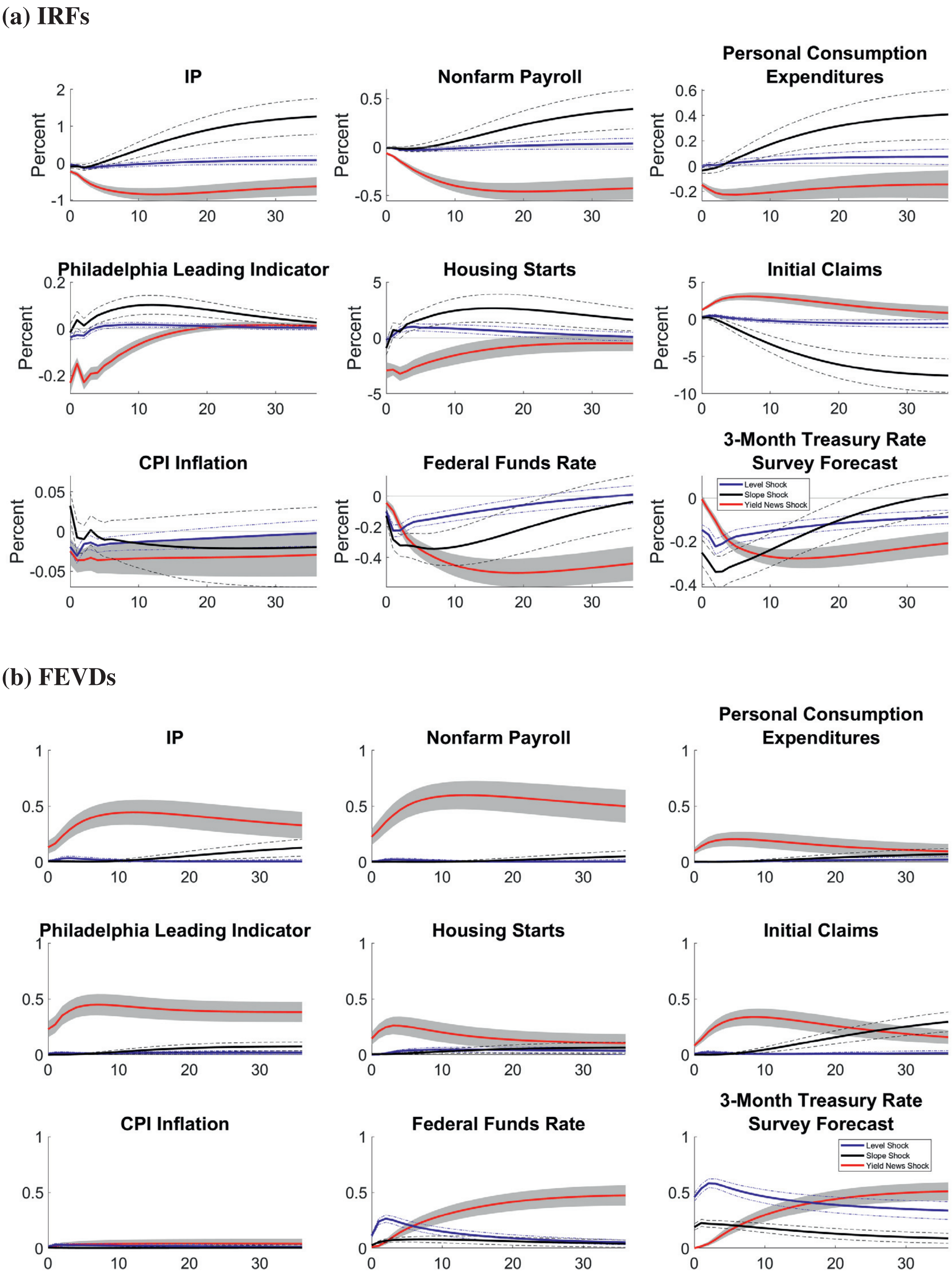
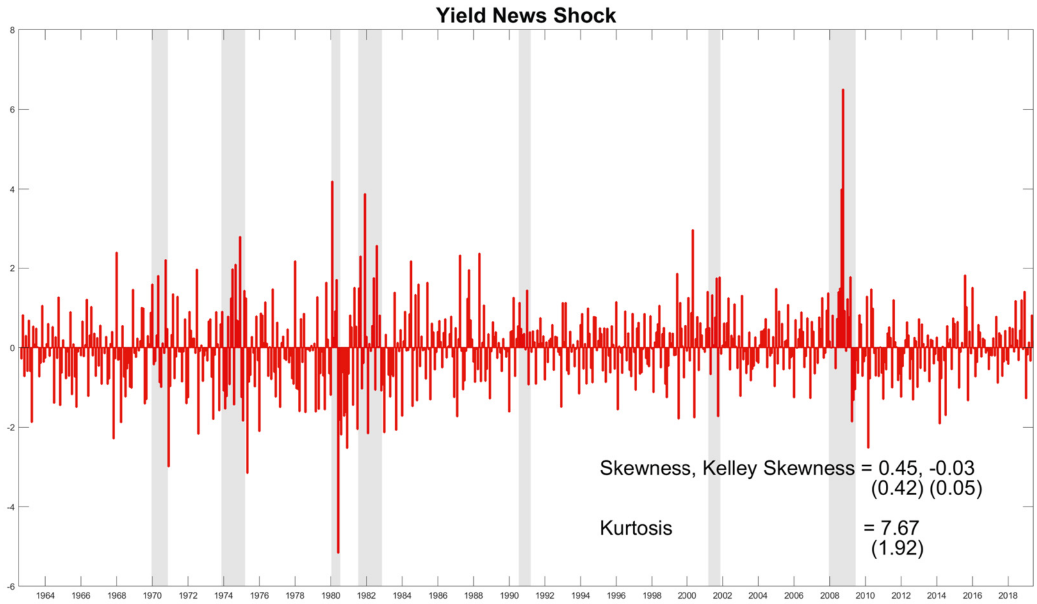


Fig. 4. IRFs and FEVDs of macroeconomic variables to yield shocks. The top panel of this figure shows the IRFs for the level shock (blue solid ±1 standard error bands), the slope shock (black solid ±1 standard error bands), and the yield news shock (red solid ±1 standard error bands) from the macro-yields model. The yield news shock is reported as a one-standard-deviation impulse, and the responses for the level and slope shocks are scaled so that they each produce the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

(a)



(b)

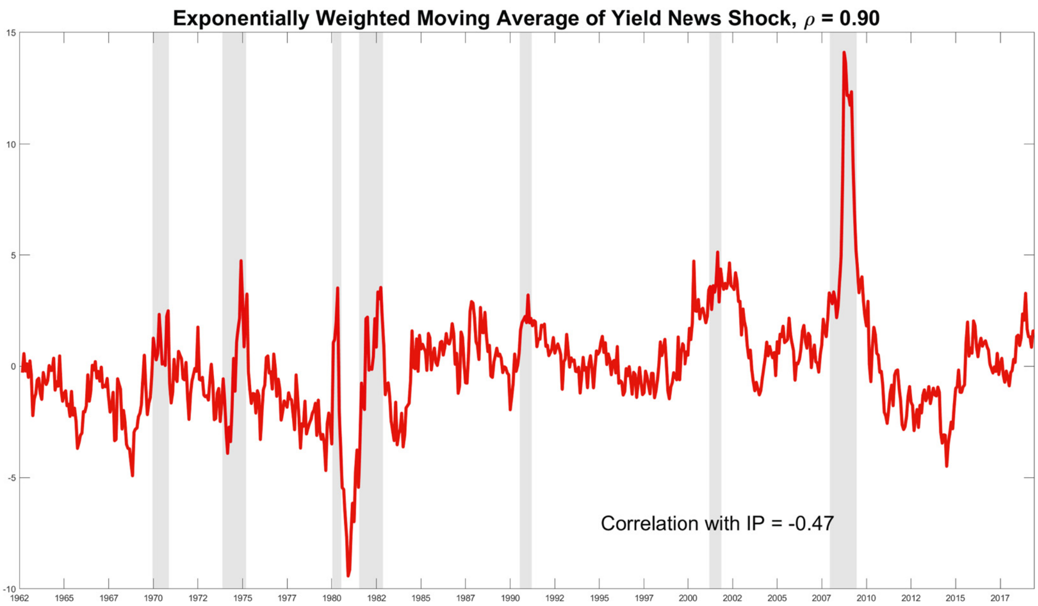


Fig. 5. Time series of estimated yield news shock. The top panel of this figure shows the estimated yield news shock, along with the skewness and kurtosis. The Kelley skewness is computed as the difference between the 90th-to-50th percentiles differential and the 50th-to-10th percentiles differential divided by the 90th-to-10th percentiles differential. The bottom panel displays the exponentially weighted moving average of the estimated yield news shock based on an AR(1) coefficient $\rho = 0.9$. Correlation is computed with 12-month IP growth. Standard errors are constructed by bootstrap resampling with 500 replications.

independent anticipations of future volatility that are associated with sharp and protracted declines of real economic activity. In light of this finding, we identify a shock to realized stock market volatility as the innovation which maximizes the one-month ahead FEV share of realized volatility. We choose this horizon to separate contemporaneous innovations to volatility from those to expectations of future volatility.

Financial market response to realized and implied volatility shocks The top panel of Fig. 6 provides the responses of the financial market indicators to the implied volatility (purple solid line) and realized volatility (blue dashed line)

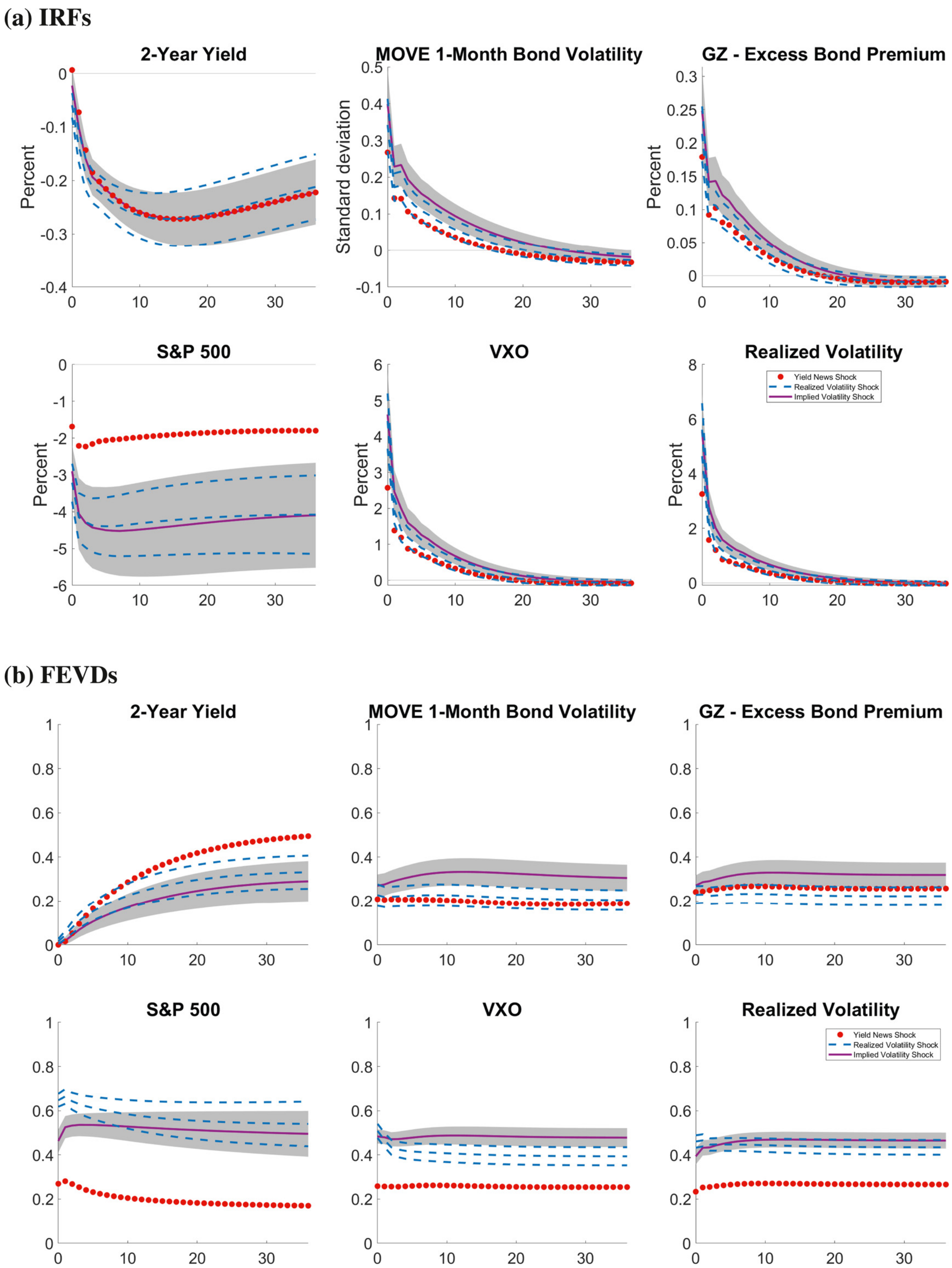


Fig. 6. IRFs and FEVDs of financial market indicators to realized and implied volatility shocks. The top panel shows the IRFs for the yield news shock (red dotted), the shock to realized volatility (blue dashed ± 1 stand error bands), and the shock to implied volatility (purple solid ± 1 stand error bands) from the macro-yields model. The yield news shock is reported as a one-standard-deviation impulse, and the responses for the realized and implied volatility shocks are scaled so that they each produce the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

shocks. For comparison, we superimpose the responses for the yield news shock.[6] The impulse responses to all three innovations are strikingly similar. They are essentially indistinguishable for the two-year Treasury yield, the MOVE, VXO and the RVol index. The responses of the S&P500 are also similar, the most important difference being that the implied and realized volatility shocks elicit a somewhat stronger stock market reaction than the yield news shock. The corresponding FEVDs shown in the bottom panel of Fig. 6 confirm these findings: yield news and shocks to implied and realized stock market volatility explain similarly large proportions of the variation in key financial indicators.

Yield response to realized and implied volatility shocks We next compare the responses of Treasury yields and their components to the three shocks. The top panel of Fig. 7 shows that while Treasury yields only feature a muted response to the shocks on impact, they drop sharply in subsequent months and persistently remain below their initial level thereafter. The impulse responses to the implied and realized volatility shocks essentially mimic those of the yield news shock which are again superimposed. As for the yield news shock, the strong delayed response of yields is primarily driven by their expected short rate component. In contrast, the term premium component rises somewhat initially, and then slowly declines over subsequent years. That said, the volatility shocks are associated with a somewhat stronger response of term premiums. The share of yield variance explained by the volatility shocks is slightly lower than for the yield news shock, as shown in the bottom panel of Fig. 7.

Importantly, the resulting responses of Treasury yields are consistent with the theoretical predictions of Bianchi et al. (2019) and Amisano and Tristani (2019). In both models, volatility follows a regime-switching process. Hence, a surprise increase of volatility tends to lead to persistently higher volatility and thus increased economic uncertainty. The higher uncertainty pushes up the term premium and via precautionary motives leads to lower expected short rates.

Macroeconomic response to realized and implied volatility shocks Fig. 8 provides the responses of our set of key macro variables to the two volatility shocks. Not surprisingly, they again closely resemble those obtained for the yield news shock. Industrial production, nonfarm payroll employment, and personal consumption expenditures all decline significantly with some delay. Leading indicators respond sharply on impact and remain elevated for one to two years. Inflation drops only slightly but persistently. The Federal Reserve responds by lowering the federal funds rate. After a few months, professional forecasters incorporate this policy response into their projections for short-term rates. The quantitative importance of the shocks for macroeconomic dynamics is highlighted in the forecast error variance decompositions in the bottom panel of Fig. 8. Similar to the yield news shock, the innovations to implied and realized stock market volatility explain about 50% of the variation in nonfarm payrolls at horizons from about one to three years. Around 30% of the federal funds rate variation at the three-year horizon is captured by the two volatility shocks, a highly significant but somewhat smaller share than that captured by the yield news shock.

These results underscore the close similarity in impulse responses of yields, their components, and macroeconomic aggregates to the shocks to realized and implied stock market volatility and the yield news shock. In the next section, we disentangle innovations to contemporaneous and expected volatility and contrast them to the yield news shock.

4.3. Uncertainty about the future or realization of current volatility?

So far, we have shown that the responses to the yield news shock and shocks to implied and realized stock market volatility are similar. Following the analysis of Berger et al. (2020), we next seek to tease out the incremental contributions of innovations to realized and implied stock market volatility to the observed responses of financial and macroeconomic variables. We do so by separately identifying the two shocks in the macro-yields DFM: a realized volatility shock as before; and an uncertainty shock identified as the innovation that explains the highest share of the forecast error variance in the VXO over the next six months, but is orthogonal to the realized volatility shock. Hence, the uncertainty shock is purged from having any impact on the realization of current volatility.[7]

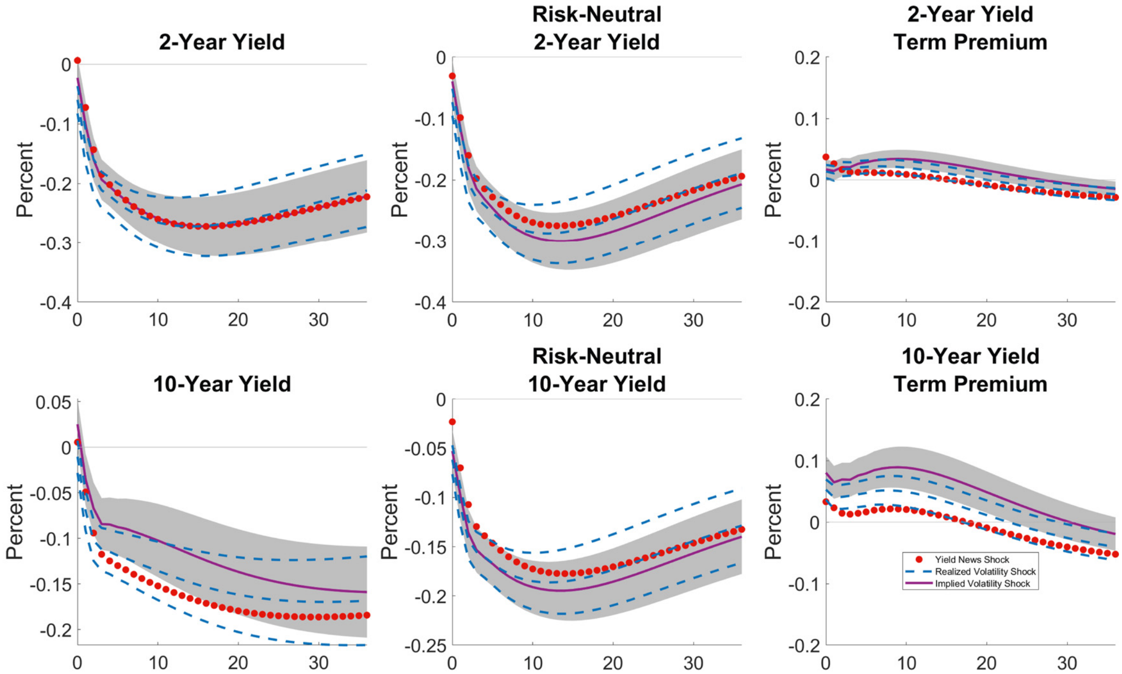
Fig. A.4 in the Online Appendix provides the results. The dashed blue and purple lines show the impulse responses for the independently identified shocks to realized and implied stock market volatility as already shown in the previous figures. The brown solid lines and associated bands show the response of the identified uncertainty shock. Looking first at the responses of the two-year yield and other financial market indicators in the top panel, we see a much more muted and somewhat short-lived response to the uncertainty shock compared to the realized volatility shock. This is also reflected in the considerably smaller variance shares explained by the uncertainty shock for all financial market indicators, as shown in the bottom panel.

Fig. A.5 in the Online Appendix provides the corresponding results for yields and their components. While the realized volatility shock leads to the previously discussed persistent and delayed decline of expected short rates and yields, the uncertainty component of implied volatility induces very different responses. Short rate ex-

[6] Consistent with the previous section, we rescale the responses to the realized and implied volatility shocks so that they each generate the same peak decline of the two-year yield as a one-standard-deviation yield news shock.

[7] We achieve identification of the two shocks sequentially. The realized volatility shock (Q_1) is identified by maximizing the share of the forecast error variance of RVol over the next month. Then, given Q_1, we identify the uncertainty shock (Q_2) by maximizing the share of forecast error variance of the VXO over the next six months, subject to $Q_2'Q_1 = 0$. As before, the responses for realized and implied volatility shocks are scaled so that they each produce the same peak decline in the two-year yield as a one-standard-deviation yield news shock. The uncertainty shock is scaled so that it has the same cumulative effect on the VXO over the next 2–60 months as the implied volatility shock.

(a) IRFs



(b) FEVDs

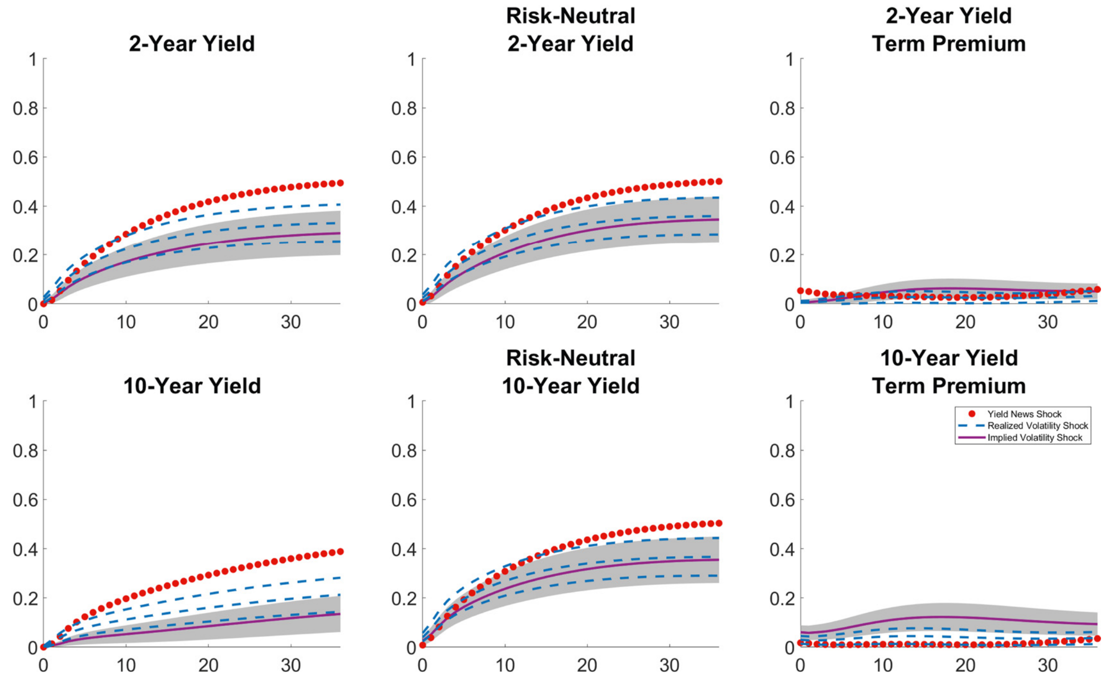


Fig. 7. IRFs and FEVDs of yields and their components to realized and implied volatility shocks. The top panel shows the IRFs for the yield news shock (red dotted), the shock to realized volatility (blue dashed ±1 stand error bands), and the shock to implied volatility (purple solid ±1 stand error bands) from the macro-yields model. The yield news shock is reported as a one-standard-deviation impulse, and the responses for the realized and implied volatility shocks are scaled so that they each produce the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

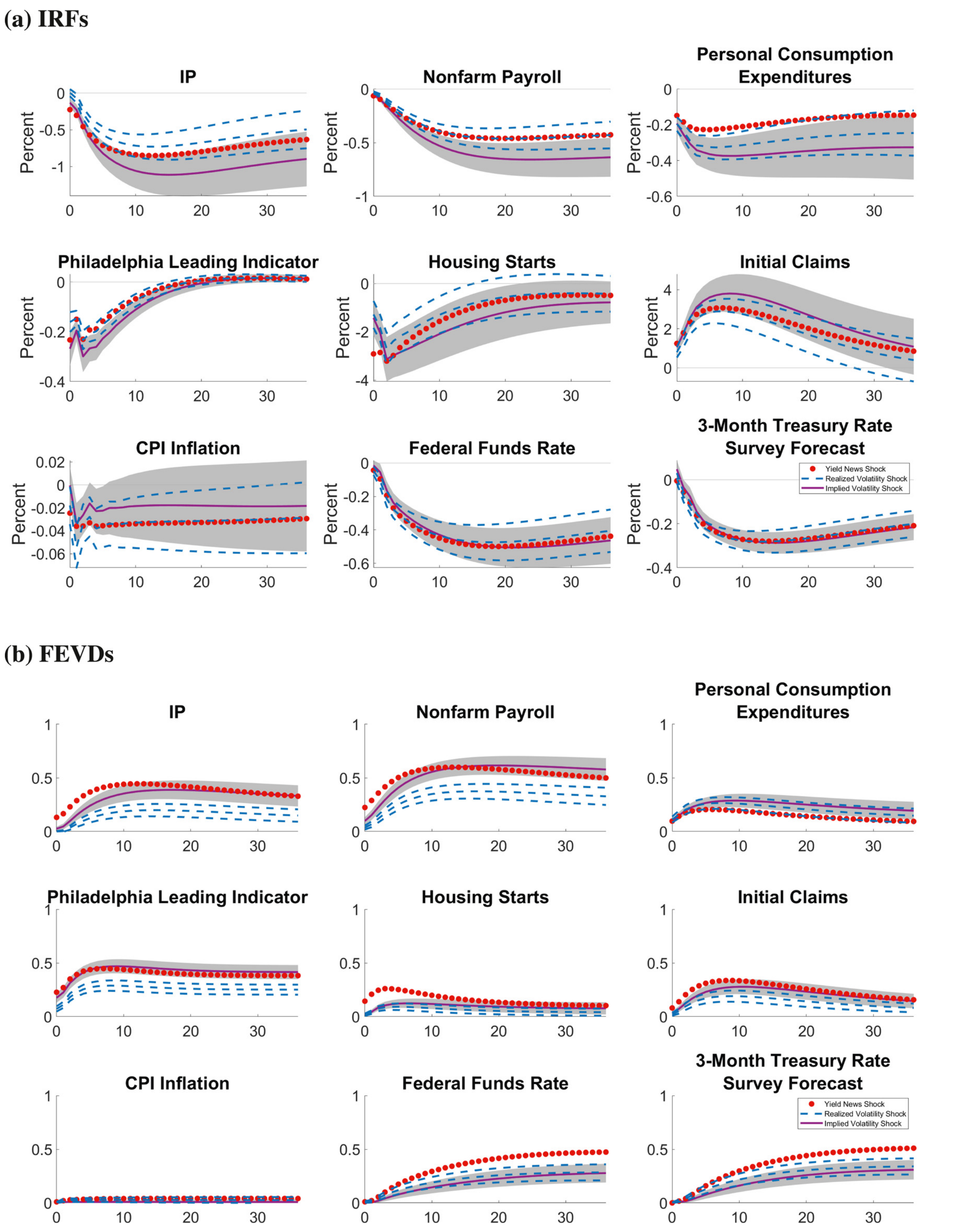


Fig. 8. IRFs and FEVDs of macroeconomic variables to realized and implied volatility shocks. The top panel shows the IRFs for the yield news shock (red dotted), the shock to realized volatility (blue dashed ±1 stand error bands), and the shock to implied volatility (purple solid ±1 stand error bands) from the macro-yields model. The yield news shock is reported as a one-standard-deviation impulse, and the responses for the realized and implied volatility shocks are scaled so that they each produce the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

pectations show a relatively mild and short-lived increase followed by a subsequent decline while term premiums persistently rise. These impulse responses are mirrored by FEV decompositions which underscore that it is the realization of stock market volatility rather than uncertainty about the future that primarily drives the observed yield curve response to increased stock market volatility.

In sum, the results in this section show that the striking similarity of the yield news shock and innovations to stock market volatility documented in the previous section is primarily driven by realized volatility and not by independent expectations of future volatility. Heightened realized stock market volatility is associated with a short-lived increase in term premiums and a persistent decrease in short rate expectations which leads to a protracted compression of yields.

4.4. News about the business cycle

We have seen in Section 4.1 that the yield news shock is also associated with a sharp contemporaneous response of leading indicators of the business cycle. This suggests that in addition to realized volatility, the effects of the yield news shock could also reflect responses to broader news about the business cycle. To shed light on this potential interpretation, we identify a business cycle news shock as the innovation that jointly maximizes the FEV shares of a set of standard leading business cycle indicators: the Philadelphia Fed leading index for the U.S. economy, initial claims for unemployment insurance, and housing starts. We set the horizon to one year ahead, a choice consistent with Angeletos et al. (2020) who argue that a shock identified this way dominates the variation of target variables (leading indicators in our case) over business cycle frequencies. As before, we scale the business cycle news shock so that it leads to the same peak decline of the two-year yield as a one-standard-deviation yield news shock.

Figs. 9 to 11 provide the results. The impulse responses and FEV decompositions of the business cycle news shock with associated error bands are shown in green, the corresponding objects for the yield news shock are superimposed as red dotted lines. Focusing first on the yields and their components in the top panel of Fig. 9, we observe a striking similarity between the two news shocks. Both lead to persistently lower yields, primarily driven by a compression of expected short rates. Moreover, both news shocks are contemporaneously hidden in yields as expected rates and term premiums feature offsetting initial responses. Although the impulse responses for the two shocks are similar, the bottom panel of Fig. 9 indicates that business cycle news explain only about half of the variation of yields compared to the yield news shock. That said, Fig. 10 shows that the responses of the other financial indicators to the two news shocks are also highly similar. The impulse responses of macro aggregates and leading indicators, provided in Fig. 11, show qualitatively similar but quantitatively more pronounced responses to the business cycle news shock. The exception is the fed funds rate and survey forecasts of the TBill rate.

These results highlight that the yield news shock is associated with macroeconomic and financial market responses that are similar to those implied by a business cycle news shock. While the yield news shock explains a larger share of variation of future yields, the business cycle news shock accounts for larger fractions of macroeconomic aggregates. In light of this finding and the observation that shocks to realized volatility also feature similar responses, a natural question is to what extent the three shocks – yield news, realized volatility, and business cycle news – are correlated. Table 3 provides the correlation coefficients between the different shocks identified in the previous sections. As shown in the third column of the table, the yield news shock is similarly strongly correlated with the realized volatility and business cycle news shocks. Both correlation coefficients are around 75%.

Fig. 12 provides plots of the realized volatility and business cycle news shocks, run through an AR(1) filter with autocorrelation coefficient of 0.9. In both charts, we superimpose the filtered yield news shock. The charts visualize the similarities between the three shock series, but they also show that they behave quite differently in certain periods. For example, around the double-dip recession of the early 1980s the yield news shock featured a sequence of negative realizations, indicating a sharp rise of expected short rates that was not associated with heightened stock market volatility or particularly positive news about the U.S. economy at the time. Instead, this likely reflected expectations of a series of rate hikes by the newly appointed Federal Reserve chairman Volcker which were hidden in yields as term premiums decreased concurrently.

The charts also document that the realized volatility and business cycle news shocks share similar time series dynamics. Table 3 confirms that they are about 60% correlated. In unreported results, we find that the shock to realized volatility and the business cycle news shock generate very different responses of the financial market and macroeconomic variables once they have been orthogonalized to one another. A realized volatility shock purged of business cycle news explains essentially none of the variation in leading indicators and real activity variables. A business cycle news shock purged of realized volatility, in turn, accounts for only a small share of the variation in stock and bond market volatility measures. Hence, while the two shocks capture partially overlapping information, they represent different sources of variability of economic and financial indicators. A regression shows that only 70% of the variation of the yield news shock is captured by the realized volatility and business cycle news shocks. This begs the question what captures the residual variation of the yield news shock.

4.5. Residual variation in yield news

To answer this question, we identify a yield news shock that is by construction orthogonal to the realized volatility and business cycle news shocks. Specifically, we include two additional orthogonality constraints in the optimization problem in Eq. (9). The resulting shock is thus the innovation which maximizes future yield variation and is orthogonal to shocks to level, slope, realized stock market volatility and business cycle news. Figs. A.6 and A.7 in the Online Appendix compare the impulse responses and

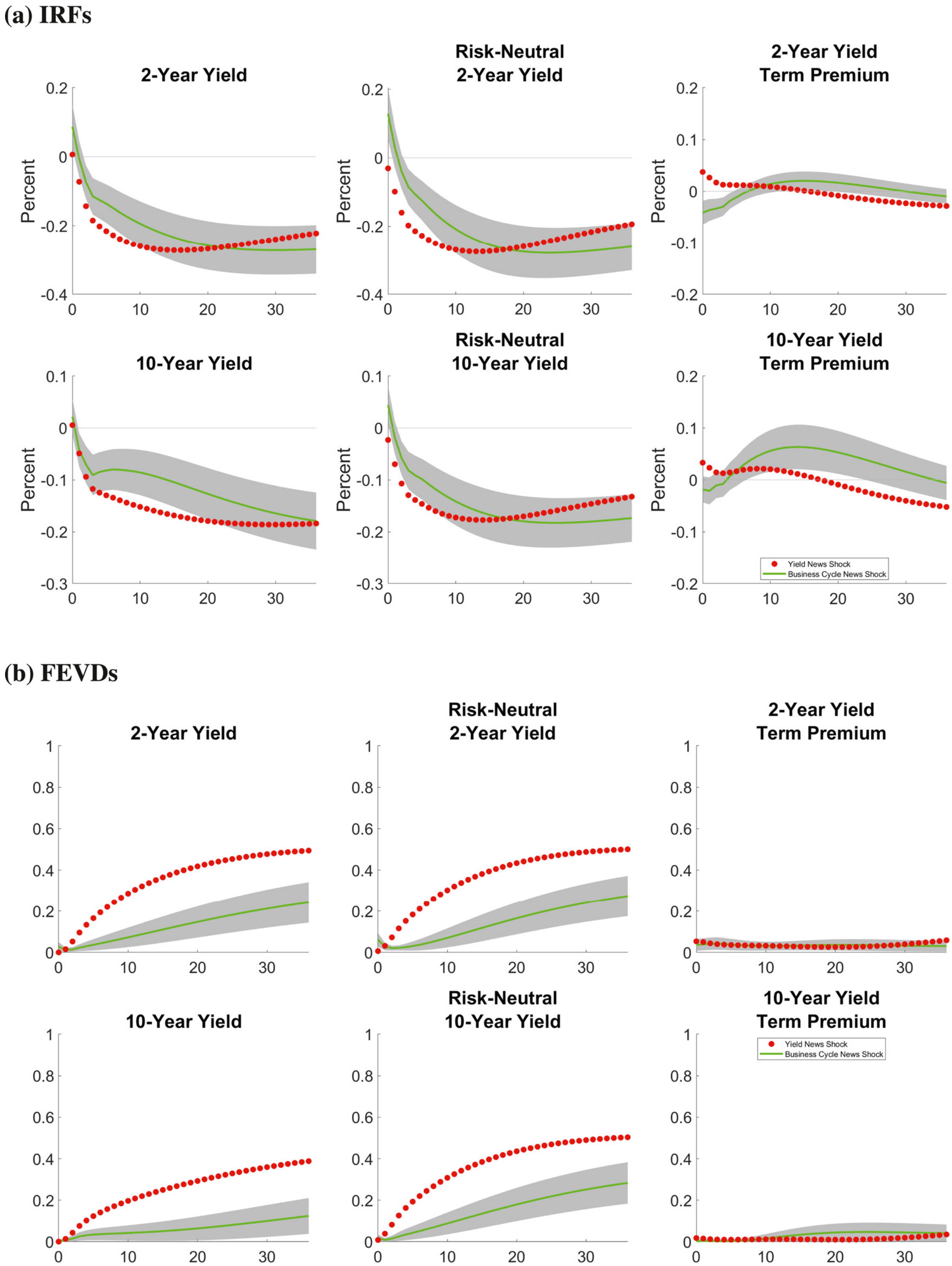


Fig. 9. IRFs and FEVDs of yields and their components to business cycle news shock. The top panel of this figure shows the IRFs for the yield news shock (red dotted), and the business cycle news shock (green solid ±1 stand error bands) from the macro-yields model. The yield news shock is reported as a one-standard-deviation impulse, and the responses for the business cycle news shock are scaled so that the shock produces the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

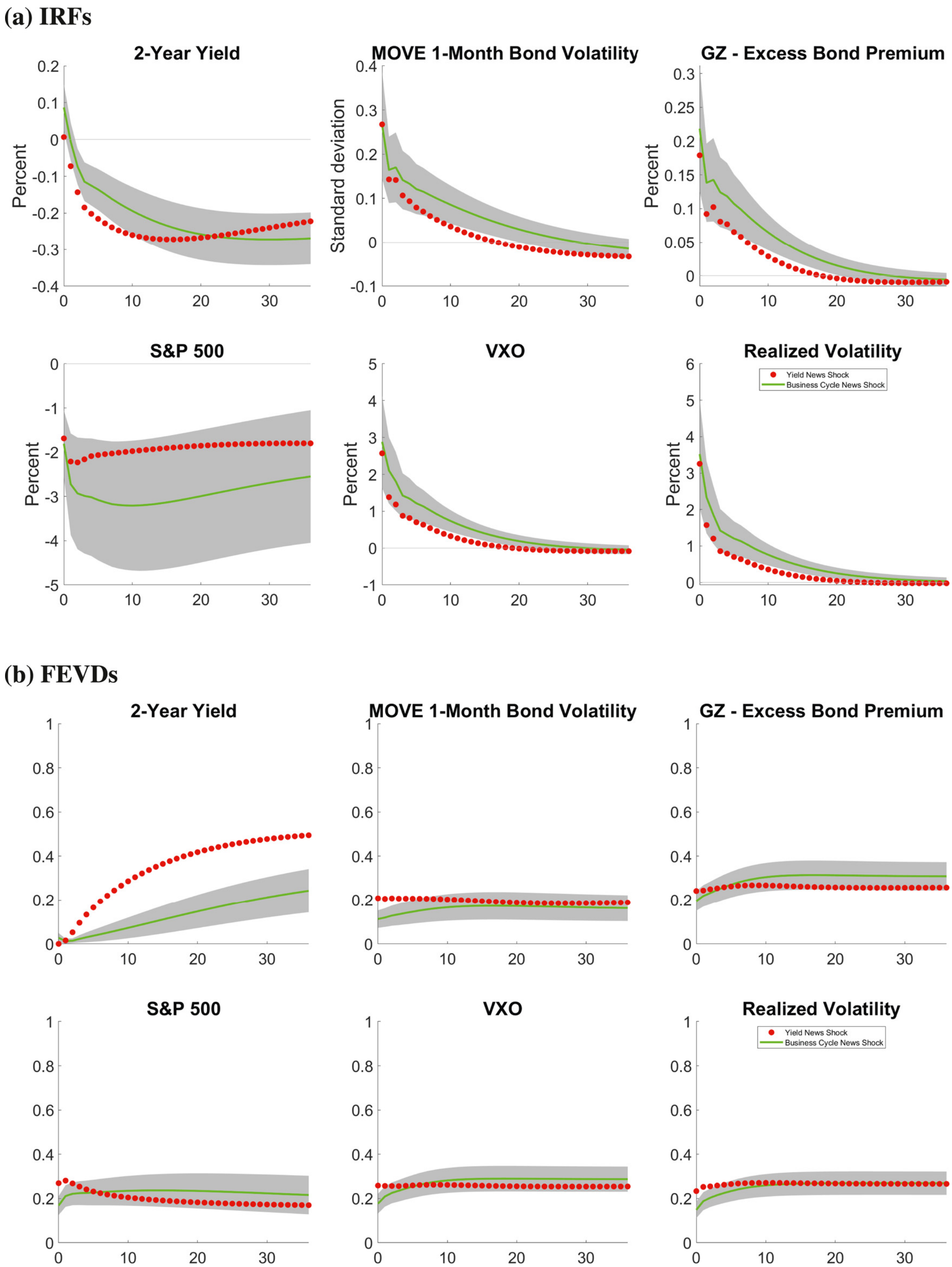


Fig. 10. IRFs and FEVDs of financial market indicators to business cycle news shock. The top panel of this figure shows the IRFs for the yield news shock (red dotted), and the business cycle news shock (green solid ±1 stand error bands) from the macro-yields model. The yield news shock is reported as a one-standard-deviation impulse, and the responses for the business cycle news shock are scaled so that the shock produces the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

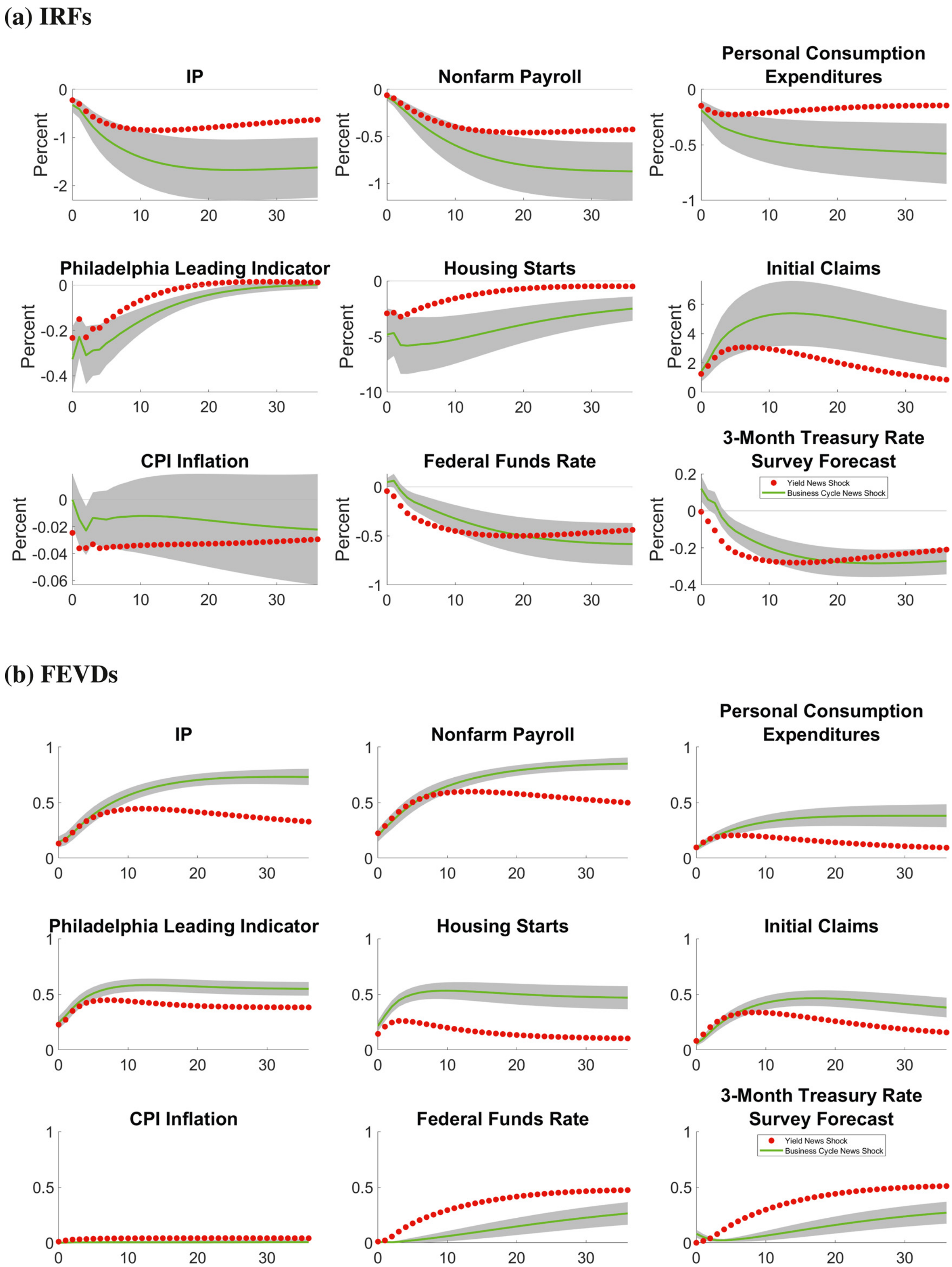


Fig. 11. IRFs and FEVDs of key macroeconomic indicators to business cycle news shock. The top panel of this figure shows the IRFs for the yield news shock (red dotted), and the business cycle news shock (green solid ±1 stand error bands) from the macro-yields model. The yield news shock is reported as a one-standard-deviation impulse, and the responses for the business cycle news shock are scaled so that the shock produces the same peak decline in the two-year yield as the yield news shock. The bottom panel displays the corresponding FEVDs.

Table 3
Correlations among estimated shocks. Entries are correlations between individually identified shocks, which are computed over the full sample 1962M7–2019M6.

	L	S	Y	VXO	RVol	BC	U	YP
Level Shock (L)	1.00							
Slope Shock (S)	0.00	1.00						
Yield News Shock (Y)	0.00	0.00	1.00					
Implied Volatility Shock (VXO)	0.03	0.10	0.74	1.00				
Realized Volatility Shock (RVol)	0.11	0.11	0.71	0.92	1.00			
Business Cycle News Shock (BC)	-0.08	-0.22	0.76	0.72	0.57	1.00		
Uncertainty Shock (U)	-0.23	-0.04	0.24	0.38	0.00	0.57	1.00	
Yield News Shock Purged of Realized Volatility & BC News (YP)	0.00	0.00	0.54	-0.09	0.00	0.00	-0.20	1.00

FEV decompositions of the original with those of the orthogonalized yield news shock. The picture emerging is that much of the financial market and macroeconomic response to the yield news shock is indeed subsumed by the other two shocks. The orthogonalized shock is associated with few significant responses and explains little to no variation in most of the considered variables. A crucial exception are Treasury yields, however, of which a significant share is captured by the orthogonalized yield news shock, especially at longer maturities and horizons.

Previous work has documented a strong comovement of global sovereign bond yields (see, e.g., Diebold et al., 2008; Adrian et al., 2018). Hence, innovations driving joint variation in international bond markets represent a candidate source of residual Treasury yield variation embedded in the yield news shock that is not captured by realized stock market volatility and U.S. business cycle news. To verify this conjecture, we study the impulse responses of yields and their components to the orthogonalized yield news shock for three major economies: Japan, Germany, and the U.K. We obtain the yield curve decompositions into expected short rate paths and term premiums from Adrian et al. (2018) who apply a four-factor version of the model in Adrian et al. (2013) to the zero coupon yield curves denominated in the respective home currency.

The impulse responses for the ten-year yield and its components are provided in the top panel of Fig. 13. The red solid line and associated bands again capture the responses to the yield news shock, the dashed yellow lines show those of the orthogonalized yield news shock. The first column shows the ten-year U.S. Treasury yield for reference. The second to fourth columns display the ten-year yields for Germany, the U.K. and Japan, respectively. They document that international bond yields respond very similarly to the U.S. yield news shock. The initial response is muted, but yields in all four economies sharply decline after a few months. While this decline is primarily driven by a compression of expected short rates in the U.S., in the other three countries term premiums also account for some of the yield decline. The bottom panel of the figure provides the associated forecast error variance decompositions. They show that the yield news shock purged from realized volatility and U.S. business cycle news explains about as much of the variation of international sovereign yields and their components as the unorthogonalized yield news shock. This suggests that news related to international bond markets account for the residual variation of Treasury yields embedded in the yield news shock.

4.6. Robustness

In this section, we document that our results are robust along several dimensions. First, we show that our yield news shock implies very different responses of macroeconomic and financial variables and explains a substantially larger fraction of Treasury yield variation than the yield curve slope shock identified in Kurmann and Otrok (2013). Second, in light of the difficulty in identifying the true factor space in bond yields documented by Crump and Gospodinov (2022), we show that the yield curve shocks that we identify from yield factors are essentially identical to a similar set of shocks identified from a VAR in individual yields. Finally, we expand this VAR to also include a small number of macroeconomic and financial market volatility variables and further estimate a macro-yields FAVAR using the VXO and realized stock market volatility as observed factors.

4.6.1. Comparison to a Kurmann and Otrok (2013) type slope shock

Thus far, we have shown that the yield news shock which explains a maximum share of future yield variation while being orthogonal to level and slope contemporaneously is highly correlated with identified shocks to financial market volatility and business cycle news. In a related paper, Kurmann and Otrok (2013, henceforth KO) identify a shock which maximizes the forecast error variance of the yield curve *slope* in a small-scale structural VAR. They show that this shock is strongly correlated with a TFP news shock, leading to a delayed but persistent increase of productivity and real output.

Since the yield news shock we identify maximizes the forecast error variance of level *and* slope, a natural question is whether it partly captures the information embedded in the Kurmann-Otrok slope shock. To compare the two shocks, we use a macro-yields DFM estimated at the quarterly frequency. All macroeconomic series are from the FRED-QD series, compiled by McCracken and Ng (2020) and essentially represents a quarterly version of the monthly dataset used in the previous sections. We add TFP growth adjusted for variations in factor utilization as updated by Fernald (2014), which is also used by KO. The model is estimated for the sample period 1962Q3-2019Q2.

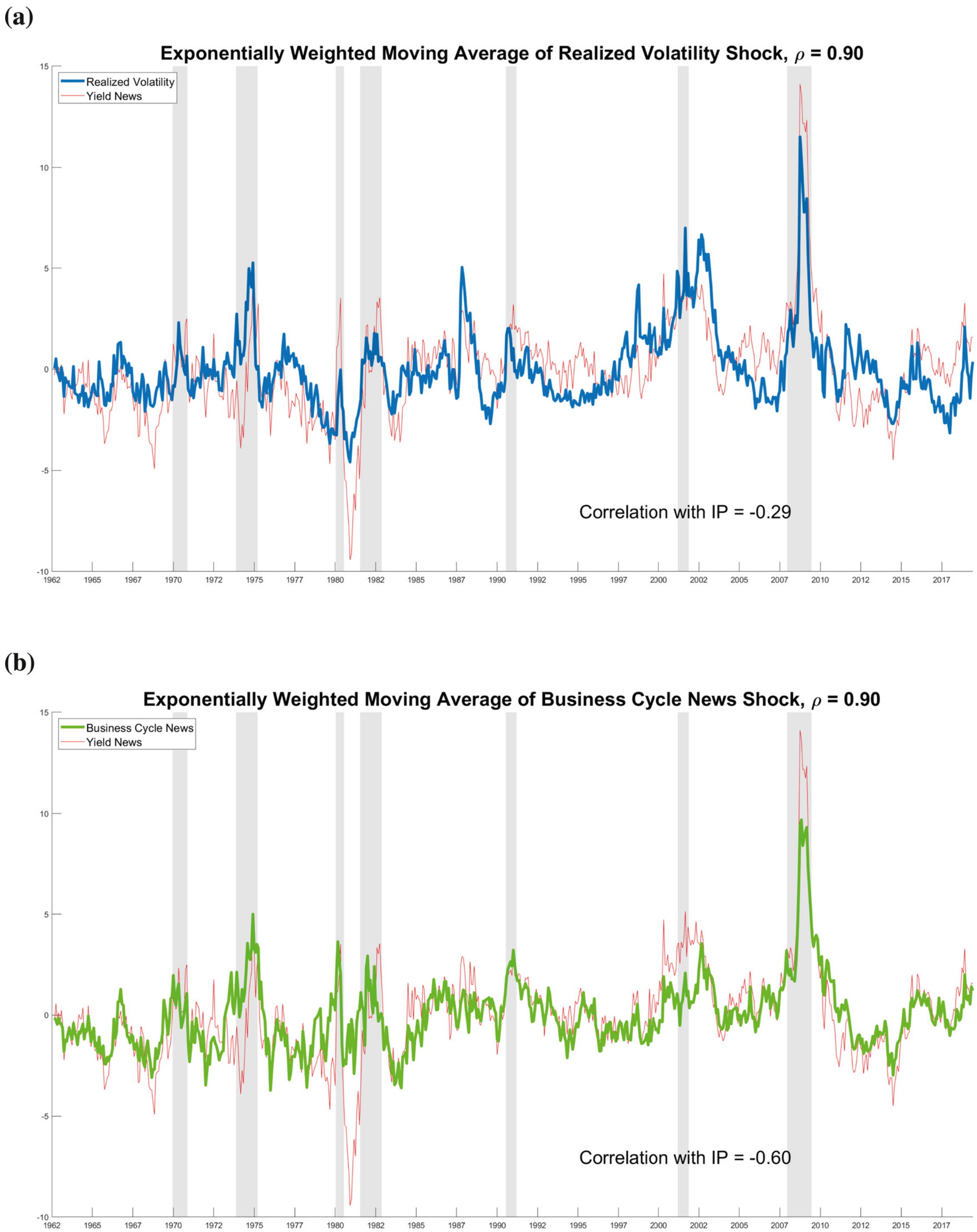


Fig. 12. Exponentially weighted moving average of estimated realized volatility and business cycle news shocks. The top panel of this figure shows the exponentially weighted moving average of the estimated yield news shock based on an AR(1) coefficient $\rho = 0.9$. The bottom panel displays that of the estimated business cycle news shock. Correlations are computed with 12-month IP growth.

The quarterly dataset is described in detail in the Online Appendix.

To make the quarterly DFM comparable to the monthly model used in the previous sections, we use the same number of five yield and eight macroeconomic factors. We identify the level, slope and yield news shocks exactly as before. We follow KO and identify a slope shock as a shock that explains a maximum share of forecast error variance of the spread between the five-year Treasury yield and the federal funds rate over a period of four quarters, the same

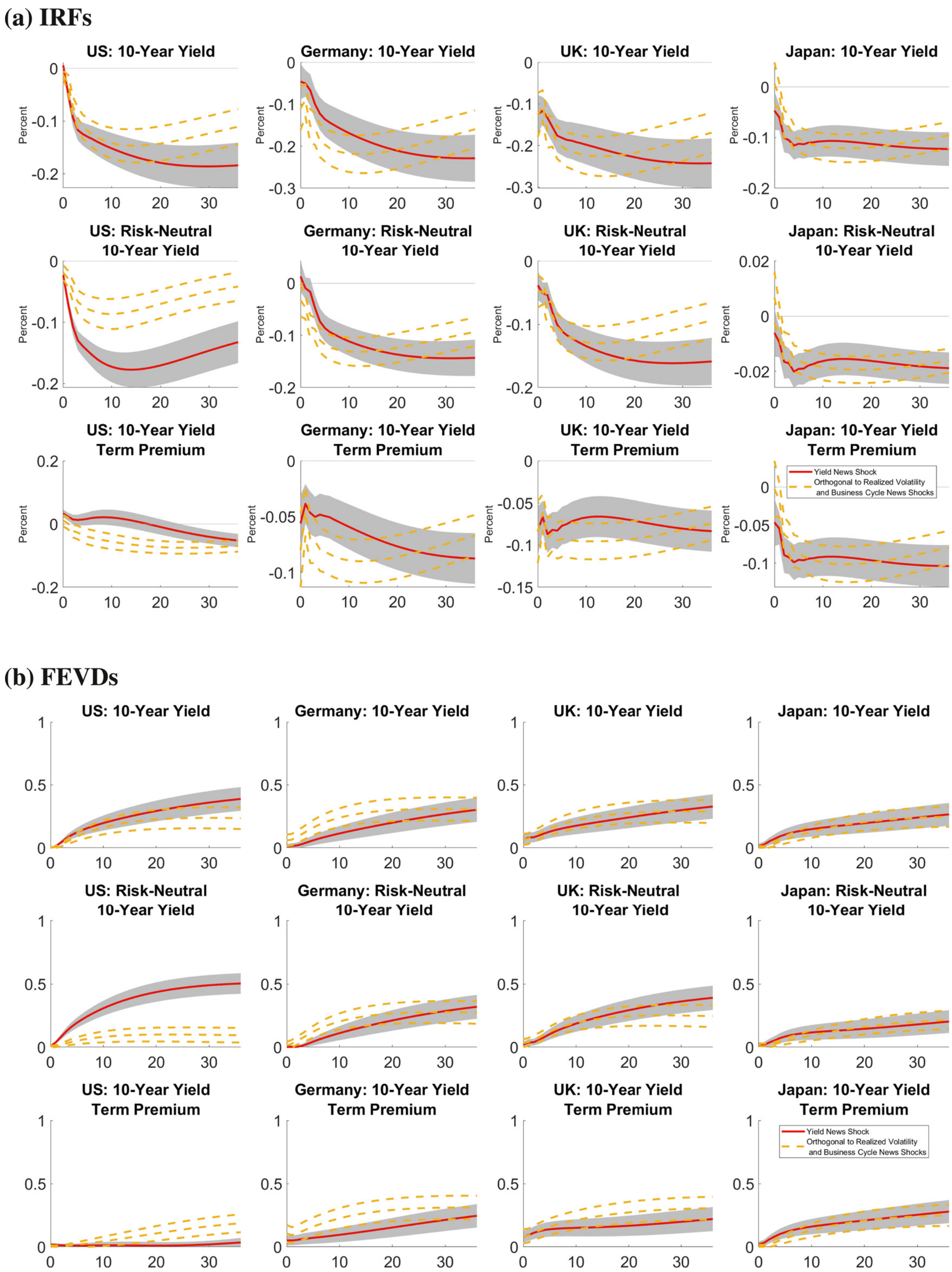


Fig. 13. IRFs and FEVDs of ten-year yield and components for the US, Germany, the UK and Japan to purged yield news shock. The top panel of this figure shows the IRFs for the yield news shock (red solid ±1 stand error bands), and the yield news shock that is made orthogonal to the realized volatility and BC news shocks (blue dashed ±1 stand error bands) from the macro-yields model. Each shock is reported as a one-standard-deviation impulse.

horizon we used to identify the yield news shock.[8] Both identification schemes are implemented in this quarterly model based on a factor VAR with one lag, selected by BIC with $1 \leq p \leq 12$.

The upper panel of Fig. A.8 in the Online Appendix provides the impulse responses for the KO slope shock in comparison to the level, slope and yield news shocks. They show that it implies impulse responses that are quantitatively and qualitatively similar to the contemporaneous slope shock we identify. The only exception is the response of TFP growth, which is considerably larger and more persistent for the KO slope shock. It is also worth noting that the KO slope shock essentially leaves financial market volatility unaffected, in sharp contrast to the yield news shock.

While the two shocks explain similar magnitudes of macro variation, the yield news shock is substantially more important for yield variation. The KO slope shock explains only about 20% of the variation in the two-year Treasury at shorter horizons while the yield news shock captures about 50% and, combined with the level shock, essentially all of the variation of yields at longer horizons. To summarize, these results show that our shock identification is very different from the one in Kurmann and Otrok (2013) and provides complementary insights into which shocks move Treasury yields and what economic interpretation these shocks have.

4.6.2. Comparison with an only-yields structural VAR

Our identification relies on the assumption that the yield news shock can be expressed as a linear combination of the innovations to a small number of factors, estimated by principal components. This identification thus requires that principal components accurately capture the true factor structure of yields. As discussed by Crump and Gospodinov (2022), this may be problematic for two reasons. First, estimates of the number of factors could be overstated because yields are highly persistent time series. Second, the fact that yields represent cross-sectional averages of one-period forward rates could lead to a spuriously small estimated number of factors. We address these concerns by identifying the yield news shock in a structural VAR which includes five variables: four Treasury yields with maturities 2, 5, 7 and 10 years, and the spread between the 10 and 1-year yields. The structural VAR identification is described in detail in Appendix A.2.

Following Stock and Watson (2016) we show that the canonical correlations between the reduced-form VAR innovations and the innovations of the DFM all exceed 0.98. Hence, essentially no information embedded in yields is lost in the factor innovations. We also compute the canonical correlations between the level, slope and yield news shocks identified from the only-yields model with the three shocks from the structural VAR. All are above 0.97, again suggesting that our use of yield principal components does not result in a loss of information relative to a model where yields are used directly. Fig. A.9 in the Online Appendix shows that the yield responses obtained from the structural VAR with five variables strongly mimic those for the level, slope and yield news shocks identified from the only-yields DFM. Hence, the difficulties in identifying the true factor structure of bond yields documented in Crump and Gospodinov (2022) do not impinge on the identification of structural shocks from yield curve factors instead of individual yields.

4.6.3. Comparison with an alternative structural VAR and FAVAR

In our baseline macro-yields DFM, the different shocks are identified as the linear combinations of factor innovations that maximize the forecast error variations of the component of the target variables that is spanned by the model factors. According to Table A.1 in the Online Appendix, yields are fully spanned by the five yield principal components, but only about half of the variation of RVol, four-fifths of that of the Philadelphia Fed leading indicator, and one-third of the variation of initial claims are explained by their common components. As the different identification approaches maximize the forecast error variation of only the common component in our baseline DFM, one may therefore be concerned that not considering idiosyncratic variation in these target variables may bias our results.

In this section, we identify realized volatility, business cycle news and yield news shocks in two alternative model specifications that target these variables directly. The first expands the five-yield structural VAR of the previous section to include eight additional financial and macroeconomic variables. These are the two stock market volatility indexes VXO and RVol, the Philadelphia Fed leading indicator, initial claims, housing starts, as well as IP, nonfarm payroll, and CPI inflation. The second alternative model is a FAVAR in which the VXO and RVol are treated as observed factors. In this specification, we also include the five Treasury yield factors and six additional macro factors, where the latter are estimated by computing the principal components of the residuals obtained from regressing all FRED-MD series on the five yield curve factors, the VXO and RVol. Because the macro-yields DFM contains 13 factors, we specify the two alternative models to have the same number of variables. We then compare the IRFs of our baseline DFM with their counterparts obtained from the two alternative model specifications. All models are estimated for the period 1962M7 to 2019M6.[9]

Fig. A.10 in the Online Appendix provides the IRFs for the yield news, realized volatility and business cycle news shocks from the DFM in comparison to the structural VAR and FAVAR specifications, where again the responses are scaled so that they each produce the same peak decline in the two-year yield. The main result of the figure is that

[8] Note that KO maximize the FEV of the yield spread over a period of ten years instead. The results are almost unchanged with respect to the identification using a horizon of four quarters.

[9] As the Philadelphia Fed leading indicator is not available before 1982, the missing observations are calculated using the expectation–maximization (EM) algorithm given in Stock and Watson (2002b). The algorithm iteratively computes the principal components from a large number of series (the FRED-MD dataset in our case) and updates missing observations using these factors. Over the post-1982 sample the Philadelphia Fed leading indicator has an R^2 of 0.84 as reported in Table A.1, and this changes to 0.91 for the full period.

the IRFs are robust to the two alternative model specifications. Hence, targeting the volatility and leading indicator variables directly rather than their common component does not alter our results.

5. Conclusion

In this paper, we jointly characterize the dynamics of a large number of macroeconomic variables and Treasury yields in a dynamic factor model. We find that three shocks explain essentially all of the variation of yields: two shocks that contemporaneously move the level and the slope of the yield curve and, importantly, a yield news shock that does not move yields initially, but captures about half of their variation at forecast horizons several years out. The impact of the news shock remains hidden in contemporaneous yields since it initially shifts their expected future short rate and term premium components in opposite directions. At the same time, the shock is associated with sharp and persistent increases in realized and implied stock and bond market volatility, a drop of stock prices, and sharp reactions of leading business cycle indicators that are followed by a protracted decline of real activity. These responses trigger an easing of monetary policy that is well understood by market participants who significantly lower their future short rate expectations, which in turn compresses yields.

We show that the yield news shock embeds several macroeconomic driving forces. First, innovations to realized stock market volatility which also lead to briefly higher term premiums and persistently lower expected short rates. Second, negative news about the U.S. business cycle also lead to a protracted decline of short rate expectations and have a sizable impact on yields in the medium run. Finally, news about international bond yields also explain significant shares of Treasury yield variation, but do not carry predictive information about U.S. macroeconomic dynamics beyond that contained in realized volatility and U.S. business cycle news.

Supplementary Material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2022.04.001.

References

Adrian, T., Crump, R. K., Durham, J. B., Moench, E., 2018. Sovereign yield comovement. Unpublished working paper.
Adrian, T., Crump, R.K., Moench, E., 2013. Pricing the term structure with linear regressions. J. Financ. Econ. 110 (1), 110–138.
Altavilla, C., Giannone, D., Modugno, M., 2017. Low frequency effects of macroeconomic news on government bond yields. J. Monet. Econ. 92, 31–46.
Amisano, G., Tristani, O., 2019. Uncertainty Shocks, Monetary Policy and Long-Term Interest Rates. Finance and Economics Discussion Series 2019-024. Washington: Board of Governors of the Federal Reserve System.
Andreasen, M.M., 2019. Explaining Bond Return Predictability in an Estimated New Keynesian Model. Aarhus University. Unpublished working paper
Angeletos, G.-M., Collard, F., Dellas, H., 2018. Quantifying confidence. Econometrica 86 (5), 1689–1726.
Angeletos, G.-M., Collard, F., Dellas, H., 2020. Business-cycle anatomy. Am. Econ. Rev. 110 (10), 3030–3070.
Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70 (1), 191–221.
Barsky, R.B., Basu, S., Lee, K., 2015. Whither news shocks? NBER Macroecon. Annu. 29 (1), 225–264.
Barsky, R.B., Sims, E.R., 2011. News shocks and business cycles. J. Monet. Econ. 58 (3), 273–289.
Basu, S., Bundick, B., 2017. Uncertainty shocks in a model of effective demand. Econometrica 85 (3), 937–958.
Beaudry, P., Portier, F., 2006. Stock prices, news, and economic fluctuations. Am. Econ. Rev. 96 (4), 1293–1307.
Berger, D., Dew-Becker, I., Giglio, S., 2020. Uncertainty shocks as second–moment news shocks. Rev. Econ. Stud. 87 (1), 40–76.
Bianchi, F., Kung, H., Tirskikh, M., 2019. The origins and effects of macroeconomic uncertainty. Duke University. Unpublished working paper
Bianchi, F., Mumtaz, H., Surico, P., 2009. The great moderation of the term structure of UK interest rates. J. Monet. Econ. 56 (6), 856–871.
Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685.
Caldara, D., Fuentes-Albero, C., Gilchrist, S., Zakrajšek, E., 2016. The macroeconomic impact of financial and uncertainty shocks. Eur. Econ. Rev. 88, 185–207.
Cochrane, J.H., Piazzesi, M., 2005. Bond risk premia. Am. Econ. Rev. 95 (1), 138–160.
Coroneo, L., Giannone, D., Modugno, M., 2016. Unspanned macroeconomic factors in the yield curve. J. Bus. Econ. Statistics 34 (3), 472–485.
Crump, R.K., Gospodinov, N., 2022. On the factor structure of bond returns. Econometrica 90 (1), 295–314.
Diebold, F.X., Li, C., 2006. Forecasting the term structure of government bond yields. J. Econom. 130 (2), 337–364.
Diebold, F.X., Li, C., Yue, V.Z., 2008. Global yield curve dynamics and interactions: a dynamic Nelson-Siegel approach. J. Econom. 146 (2), 351–363.
Diebold, F.X., Rudebusch, G.D., Aruoba, S.B., 2006. The macroeconomy and the yield curve: a dynamic latent factor approach. J. Econom. 131 (1–2), 309–338.
Duffee, G.R., 2011. Information in (and not in) the term structure. Rev. Financ. Stud. 24 (9), 2895–2934.
Fernald, J., 2014. A Quarterly, Utilization-Adjusted Series on Total Factor Productivity. Federal Reserve Bank of San Francisco. Working Paper 2012-19
Feunou, B., Fontaine, J.-S., 2018. Bond risk premia and Gaussian term structure models. Manag. Sci. 64 (3), 1413–1439.
Forni, M., Gambetti, L., 2010. The dynamic effects of monetary policy: a structural factor model approach. J. Monet. Econ. 57 (2), 203–216.
Forni, M., Gambetti, L., Sala, L., 2014. No news in business cycles. Econ. J. 124 (581), 1168–1191.
Forni, M., Giannone, D., Lippi, M., Reichlin, L., 2009. Opening the black box: structural factor models with large cross sections. Econom. Theory 25 (5), 1319–1347.
Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2000. The generalized dynamic-factor model: identification and estimation. Rev. Econ. Stat. 82 (4), 540–554.
Francis, N., Owyang, M.T., Roush, J.E., DiCecio, R., 2014. A flexible finite-horizon alternative to long-run restrictions with an application to technology shocks. Rev. Econ. Stat. 96 (4), 638–647.
Garbade, K.D., 1996. Fixed Income Analytics. Mit Press.
Ghysels, E., Horan, C., Moench, E., 2018. Forecasting through the rearview mirror: data revisions and bond return predictability. Rev. Financ. Stud. 31 (2), 678–714.
Giglio, S., Kelly, B., 2018. Excess volatility: beyond discount rates. Q. J. Econ. 133 (1), 71–127.
Gilchrist, S., Zakrajšek, E., 2012. Credit spreads and business cycle fluctuations. Am. Econ. Rev. 102 (4), 1692–1720.
Gorodnichenko, Y., Lee, B., 2020. Forecast error variance decompositions with local projections. J. Bus. Econ. Stat. 38 (4), 921–933.
Gurkaynak, R.S., Kisacikoğlu, B., Wright, J.H., 2020. Missing events in event studies: identifying the effects of partially measured news surprises. Am. Econ. Rev. 110 (12), 3871–3912.
Gurkaynak, R.S., Sack, B., Wright, J.H., 2007. The U.S. treasury yield curve: 1961 to the present. J. Monet. Econ. 54 (8), 2291–2304.
Hanson, S.G., Lucca, D.O., Wright, J.H., 2021. Rate-amplifying demand and the excess sensitivity of long-term rates. Q. J. Econ. 136 (3), 1719–1781.
Joslin, S., Priebsch, M., Singleton, K.J., 2014. Risk premiums in dynamic term structure models with unspanned macro risks. J. Financ. 69 (3), 1197–1233.
Kurmann, A., Otrok, C., 2013. News shocks and the slope of the term structure of interest rates. Am. Econ. Rev. 103 (6), 2612–2632.

Litterman, R., Scheinkman, J., 1991. Common factors affecting bond returns. Journal of Fixed Income 1 (1), 54–61.
Ludvigson, S.C., Ma, S., Ng, S., 2021. Uncertainty and business cycles: exogenous impulse or endogenous response? Am. Econ. J. Macroecon. 13 (4), 369–410.
Ludvigson, S.C., Ng, S., 2009. Macro factors in bond risk premia. Rev. Financ. Stud. 22 (12), 5027–5067.
McCracken, M.W., Ng, S., 2016. FRED-MD: a monthly database for macroeconomic research. J. Bus. Econ. Stat. 34 (4), 574–589.
McCracken, M.W., Ng, S., 2020. FRED-QD: A quarterly database for macroeconomic research. Federal Reserve Bank of St. Louis. Working Paper
Moench, E., 2008. Forecasting the yield curve in a data-rich environment: a no-arbitrage factor-augmented VAR approach. J. Econom. 146 (1), 26–43.
Sargent, T.J., Sims, C.A., 1977. Business cycle modeling without pretending to have too much a priori economic theory. New Methods in Business Cycle Research 1, 145–168.
Stock, J.H., Watson, M.W., 2002. Forecasting using principal components from a large number of predictors. J Am Stat Assoc 97 (460), 1167–1179.
Stock, J.H., Watson, M.W., 2002. Macroeconomic forecasting using diffusion indexes. J. Bus. Econ. Stat. 20 (2), 147–162.
Stock, J.H., Watson, M.W., 2016. Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. Handbook of Macroeconomics, Vol. 2. Elsevier, pp. 415–525.
Uhlig, H., 2003. What moves real GNP?. Euro Area Business Cycle Network. Unpublished working paper