Common shocks in stocks and bonds

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Using joint variation in the stock market and the Treasury yield curve, we provide a new approach to identify shocks to investors' expectations of monetary policy and economic growth as well as pure risk-premium shocks. Tracing out the effects of those shocks day-by-day, we explain the puzzling fact why stocks *but not* bonds earn high returns on Federal Open Market Committee (FOMC) announcement days and over the FOMC cycle. About 70% of the average positive stock returns earned over the FOMC cycle stems from the declining premiums, with the remaining 25% explained by accommodating monetary news, and only a small fraction by positive growth news. As bonds hedge growth risk in stocks, the signs of their responses to news are ambiguous: FOMC-induced reductions in the value of the bond insurance premium nearly completely offset any gains, making overall bond returns economically small. Since the mid-1980s, conventional monetary news accounts for about 40% of the variation in the two-year yield, but less than 10% and 20% of the variation in the ten-year yield and the aggregate stock market, respectively. The results suggest that the Fed has a significant effect on long-term assets through its ability to affect the risk premiums. (*JEL*: E43, E44, G12, G14)

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I. Introduction

What are the common economic shocks driving the stock market and Treasury yield curve? While asset pricing models predict a tight link between the sources of variation in stocks and bonds, such link has been more difficult to establish empirically. Correlations between stocks and bond returns are not stable over time and switch sign (e.g., Baele, Bekaert, and Inghelbrecht, 2010; Campbell, Sunderam, and Viceira, 2017). Countercyclical variation typically found in the equity risk premium is much less clear for bonds, whose expected returns tend to vary at a frequency higher than the business cycle. Accordingly, successful predictors of stock returns have poor predictive power for bond returns and vice versa. Perhaps even more puzzling is the reaction of stocks and bonds to central bank decision announcements and various other forms of communication. Stocks but not long-term bonds earn high returns ahead of scheduled Federal Open Markets Committee (FOMC) announcements (Lucca and Moench, 2015) as well as at regular intervals between those announcements when the Fed's decision making takes place (Cieslak, Morse, and Vissing-Jorgensen, 2019). At the same time, bonds but not stocks respond strongly to tightly identified Fed communication shocks that reveal information about the future policy path (Gürkaynak, Sack, and Swanson, 2005a).

In this paper, we reconcile these facts by decomposing the variation in the U.S. aggregate stock market and the Treasury yield curve into orthogonal shocks which have an intuitive economic interpretation. Specifically, we isolate growth news, monetary news, and two distinct shocks generating time-varying risk premiums as common drivers of stocks and yields, recognizing that stocks and yields are differentially exposed to those shocks.[1] For one, good news about the real activity (positive growth news) raises both stock prices and yields, and good monetary news (easing) raises stock prices but depresses yields. Important for our conclusions is the identification of two risk-premium shocks that differ in the direction of the comovement between stocks and yields that they generate. Shocks that produce a common variation in equity and bond risk premium reflect the fact that stocks and bonds are both exposed to the pure discount rate news. Shocks that drive risk premiums on stocks and bonds in opposite directions arise from bonds providing a hedge for cash-flow risk in stocks. We refer to these shocks as the common premium and the hedging premium, respectively. Both premium shocks work to affect stock prices in the same direction (positive shocks

[1] Note that we refer to the direction of the comovement of stocks returns with *yield* changes rather than with bond returns. Negative comovement of stocks returns with yield changes implies a positive comovement of stock and bond returns.

lower stock prices), but they have opposite effects on bonds (a positive common-premium shock lowers bond prices and raises yields, while a positive hedging-premium shock does the opposite).

Our identification strategy involves two sets of restrictions—on the comovement between stocks and yields and on the effect that different economic shocks have on the yield curve across maturities. The cross-maturity restrictions serve to separate shocks to short-rate expectations from shocks to the risk premium. The restrictions on the comovement of stocks and yields further distill shocks to short-rate expectations into monetary and growth news exposures and the risk-premium shocks into an exposure that is common to stocks and bonds and a hedging component whereby bonds serve to insure risk in stocks. The cross-maturity restrictions derive from the identity that long-term yields are conditional expectations of average future short rates plus the risk premium. To the extent that shocks to short-rate expectations—monetary and growth news in our setting—are mean reverting (although can be persistent), they affect the short end of the yield curve more strongly than they do the long end. The strength of relative responses of yields at different maturities can be exploited to isolate the risk-premium shocks. Absent risk-premium shocks, it is hard to rationalize why some news impacts predominantly yields at longer maturities (e.g., Hanson and Stein, 2015).

We implement the above ideas via sign restrictions drawing on a large literature on structural vector autoregressions.[2] Sign restrictions allow us to convert reduced-form innovations in asset prices into structural shocks that have a particular economic interpretation without imposing parametric structure of a fully-specified asset pricing model. Using information from asset prices alone, we obtain structural shocks at the daily frequency over a period spanning nearly four decades. The ability to decompose the variation in stocks and yields on any day—as opposed to specific events or announcement dates—is important for assessing the overall effects that different shocks have on asset prices. The case of Fed communication illustrates this point. The identification of monetary shocks typically relies on the timing of the Fed announcements and the assumption that the announcements reveal pure monetary policy news. Neither of the assumptions needs to hold in practice. Monetary news can come out outside of scheduled events, and the Fed communication can lead investors to

[2]See e.g., Faust (1998), Uhlig (2005), Rubio-Ramirez et al. (2010), Arias et al. (2019), Ludvigson et al. (2019), as well as Fry and Pagan (2011) and Kilian and Lütkepohl (2017) for reviews of this literature.

update their beliefs about state of the economy or uncertainty rather than just policy.[3] Our approach circumvents issues which emerge in identification via the timing of events and, instead, extracts the news from asset prices using economically motivated restrictions that should hold on any day. To validate the identified shocks, we perform comparisons with results from event studies, survey expectations, and various measures of equity and bond risk premium.

With estimated contributions of shocks to asset prices, we revisit the behavior of stocks and bonds around the FOMC announcements and over the full cycle between FOMC meetings. From 1994 to 2017, the average close-to-close stock market return on FOMC days is highly significant at 28 basis points (bps); in contrast, the average return on the ten-year Treasury bond is insignificant at 5 bps, consistent with the results that Lucca and Moench (2015) obtain for the 1994–2011 sample. The decomposition of asset prices into structural shocks permits a more nuanced interpretation of this evidence. We find that reductions in the common risk premium contribute to raise both stock and bond prices on FOMC days, with accommodating monetary news having a smaller but still significant effect. For stocks, the risk-premium shocks generate nearly 70% of the average FOMC day returns, while monetary shocks account for another 25%. Importantly, the individual shocks have a significant impact on bonds as well. Reductions in the common premium increase the FOMC day return on the ten-year Treasury by 8 bps, and negative monetary shocks add another 3 bps. However, those gains are offset by the decline in the hedging premium, which depresses bond prices, and thus makes the overall response in bonds economically small and statistically insignificant.

The finding that the risk-premium variation is the primary channel for high stock returns on FOMC days is consistent with the interpretation in Cieslak, Morse, and Vissing-Jorgensen (2019, CMVJ). CMVJ document that the FOMC day returns are part of a regular pattern of high average stock returns earned in "even weeks" in the FOMC cycle time. Analyzing the timing of various Fed events, they argue that this pattern is causally related to the Fed's decision making and works through the Fed being able to affect the risk premiums. Indeed, CMVJ document that equity risk premiums (measured following Martin (2017)) decline significantly in even weeks, thus contributing to positive stock returns. Our identification provides independent verification of those results as it does not involve assumptions about

[3]The information content of central bank communication is subject of a growing literature, e.g., Campbell et al. (2012), Hanson and Stein (2015), Nakamura and Steinsson (2018), Swanson (2018), Cieslak and Schrimpf (2019), Jarocinski and Karadi (2019).

the timing of the Fed's actions or communication. We find that while even weeks in FOMC cycle time are indeed associated with more news of monetary accommodation, the impact of negative risk-premium shocks is about 3.5 times stronger than that of pure monetary shocks. The reason why bonds do not display strong reactions over the FOMC cycle is analogous to FOMC days. Although common premium and monetary shocks contribute to positive bond returns in even weeks, the hedging premium and (to some extent) growth news offset that effect, leading to what appears as a lack of response in bonds.

Beyond the FOMC effects, our approach allows us to analyze the overall importance of different shocks for the dynamics of stocks and yields, as well as the sources of the changing stock-yield comovement over the past three and a half decades. Using variance decompositions of daily yield changes and stocks returns, we show that from 1983 to 2017, about 80% of the variance of the two-year yield changes is driven by monetary and growth news (each roughly equal in shares); these proportions reverse for the ten-year yield changes which to 80% is explained by premium shocks (split into a 45% contribution of common premium shocks and 35% hedging premium shocks). The risk-premium shocks explain more than 50% of the variation in stock returns, with additional 25% due to growth news and less than 20% due to monetary shocks. Analyzing the sources of the time-varying comovement between stocks and yields, we attribute the change in correlations in the late 1990s to a diminished role of the common risk premium and monetary shocks (both of which drive stocks and yields in the opposite direction), and increased importance of growth and, in particular, hedging premium shocks (both of which drive stocks and yields in the same direction).

Related literature

We build on a large body of work that studies the comovement between stocks and bonds. Andersen et al. (2007) and Connolly et al. (2005) document that the direction of the comovement between stocks and yields changes sign over time. A number of authors develop macro-finance models to investigate the joint pricing of stocks and bonds (e.g., Bekaert et al. (2009), Bekaert et al. (2010b), Burkhardt and Hasseltoft (2012), Campbell et al. (2017), Campbell et al. (2019), Koijen et al. (2017), Lettau and Wachter (2011), Song (2017)). Baele et al. (2010) show that exposures to observable macroeconomic variables explain a relatively small fraction of the stock-bond correlations over time, and suggest that risk premiums drive a significant part of the comovement. We rely on these insights to propose a set of economic shocks to investors' beliefs about the fundamentals and shocks to risk prices to isolate their effects on stocks and yields. In contrast with the literature, our empirical approach does not specify a particular parametric model. We instead impose restrictions on innovations in asset prices to identify shocks with a particular economic interpretation.

A growing literature uses the comovement of stocks and yields as an identification tool to distinguish types of news (Matheson and Stavrev (2014), Cieslak and Schrimpf (2019), and Jarocinski and Karadi (2019)). We contribute to that literature in several ways. Most importantly, we exploit the cross-section of yields to isolate the risk-premium shocks. Jarocinski and Karadi (2019) and Matheson and Stavrev (2014) focus on a single yield maturity without taking a stance on the variation in the risk premiums. Cieslak and Schrimpf (2019) take a step toward the identification of risk-premium shocks, but do not distinguish their different sources, and concentrate their analysis only on central bank communication in narrow event windows. We show that accounting for two dimensions in risk-premium shocks is important for understanding the stock-yield comovement.

The paper is structured as follows. Section II contains the conceptual framework. Section III discusses the identification approach along with the literature that motivates it. Section IV studies the economic drivers of stocks and bonds over the FOMC cycle. Section V analyzes the contributions of the different shocks to the overall variation in stocks and yields, and studies the dynamic effects of shocks on asset prices. Section VI validates the interpretation of structural shocks that we identify. Section VII concludes.

II. Conceptual framework

II.A. A structural VAR interpretation of asset pricing models

To which degree are movements in asset prices driven by shocks to investors' beliefs about economic activity, monetary policy, or by pure risk-premium shocks that are uncorrelated with fundamentals? The ability to answer such questions requires an identification of shocks to economically interesting state variables and the knowledge of how they affect the asset price dynamics.

Asset prices (e.g., bond yields, log price/dividend ratios) are frequently modelled as affine functions of the state variables.[4] Let Y_t be the vector of asset prices, and F_t be the vector of state variables. For simplicity, assume that Y_t contains as many elements as there are state

[4] Or approximately affine, as for example, the commonly used approximation arises due to Campbell and Shiller (1988) linearization for the log price-dividend ratio.

variables F_t, k, then

$$Y_t = a + AF_t, \tag{1}$$

where $a_{(k\times 1)}$ and $A_{(k\times k)}$ are functions of parameters that characterize the dynamics of the state of the economy and investors' preferences. Suppose that Y_t evolves according to a vector autoregression (VAR)

$$Y_t = \mu_Y + \Psi(L)Y_t + u_t, \tag{2}$$

where $\Psi(L)$ is the polynomial in the lag operator L, $\Psi(L) = \sum_{i=1}^{p} \Psi_i L^i$, and shocks u_t have a variance-covariance matrix $Var(u_t) = \Omega_u$. When matrix A is invertible, substituting (1) into (2) implies the dynamics for the state variables, F_t,

$$F_t = \mu_F + \Phi(L)F_t + \nu_t \tag{3}$$

where $\mu_F = A^{-1}(\mu_Y - (I - \Psi(L))a)$, $\Phi_i = A^{-1}\Psi_i A$, and $\nu_t = A^{-1}u_t$.

Equation (2) is the reduced-form representation and equation (3) is the structural-form representation of asset price dynamics. We assume that shocks to the state variables are mutually uncorrelated, $\nu_t = \Sigma_F \omega_t$ with Σ_F diagonal matrix, and ω_t are unit-variance shocks, $Var(\omega_t) = I$, with I identity matrix. Matrix A represents the contemporaneous responses of asset prices to structural shocks and is identified up to the scaling by the volatility of the structural shocks. Thus, innovations to asset prices, $Y_t - E_{t-1}(Y_t) = u_t$, are

$$u_t = \tilde{A}\omega_t, \quad \text{with} \quad \tilde{A} = A\Sigma_F. \tag{4}$$

While we can obtain u_t as residuals from the reduced-form VAR (2), the identification of the $\tilde{A}$ matrix, and hence of structural shocks ω_t, requires additional restrictions. We exploit the fact that the structure of $\tilde{A}$ is directly linked to the cross-section of asset prices, and the literature provides substantial prior knowledge about its properties. One source of guidance comes from theory; another source comes from the empirical evidence on the identification of structural shocks (e.g., event studies). Both can be used to impose restrictions on the elements of the $\tilde{A}$ matrix, as we discuss in more detail in Section III.

II.B. Model illustration

Asset pricing models usually start with the dynamics of the state variables and assumptions about the stochastic discount factor which jointly imply the dynamics of asset prices. Under the null of a specific model, there exists a unique $\tilde{A}$ matrix in (4) as a function of model parameters. Before moving onto the empirical implementation, we thus illustrate the effect of economic shocks of interest in a simple model of stocks and yields.

The state variables evolve according to a VAR(1)

$$F_{t+1} = \mu_F + \Phi_F F_t + \Sigma_F \omega_{t+1} \tag{5}$$

where F_t, with Φ_F stable, contains expected inflation τ_t, expected growth rate of the economy g_t, a monetary policy shock m_t, and two state variables driving market prices of risk x_t^+, x_t^-, $F_t = (\tau_t, g_t, m_t, x_t^+, x_t^-)'$. Shocks $\omega_t = (\omega_t^\tau, \omega_t^g, \omega_t^m, \omega_t^{x^+}, \omega_t^{x-})'$ are independent and normally distributed $N(0,1)$, and Σ_F is a diagonal matrix. The nominal one-period interest rate is determined by:

$$i_t = \delta_0 + \delta_\tau \tau_t + \delta_g g_t + m_t = \delta_0 + \delta_1' F_t, \tag{6}$$

where $\delta_1 = (\delta_\tau, \delta_g, \delta_m, 0, 0)'$ and we use the normalization $\delta_m = 1$ for monetary shocks. Equation (6) can be thought of as a forward looking Taylor rule. The log nominal stochastic discount factor (SDF) has the form:

$$\ln M_{t+1} = -i_t - \frac{1}{2}\Lambda_t' \Lambda_t - \Lambda_t' \omega_{t+1}, \tag{7}$$

where $\Lambda_t = \Sigma_F^{-1}(\lambda_0 + \Lambda_1 F_t)$. The realized inflation is $\pi_{t+1} = \tau_t + \sigma_\pi \varepsilon_{t+1}^\pi$ and the realized real dividend growth is $\Delta d_{t+1} = g_t + \sigma_d \varepsilon_{t+1}^d$, and we assume that shocks $\varepsilon_{t+1}^\pi, \varepsilon_{t+1}^d$ are not priced. The nominal log SDF $\ln M_{t+1}$ is linked to the real log SDF $\ln M_{t+1}^r$ and inflation by $\ln M_{t+1} = \ln M_{t+1}^r - \pi_{t+1}$.

With the assumptions about the state dynamics, the short rate, and the SDF, the continuously compounded yield on the n-period nominal bond ($y_t^{(n)}$) and the log price-dividend ratio (pd_t) are affine functions of the state:

$$y_t^{(n)} = b_n + B_n' F_t \tag{8}$$

$$pd_t = b_s + B_s' F_t, \tag{9}$$

where $y_t^{(1)} = i_t$ and $pd_t = s_t - d_t$ with s_t denoting the log stock market index and d_t denoting log level of dividends. Coefficients B_n and B_s have the well-known form provided in Internet Appendix A. Bond prices $P_t^{(n)}$ and yields are related by $\ln P_t^{(n)} = -ny_t^{(n)}$. Thus, news that raises yields, lowers bond prices. Innovations to yields are $y_{t+1}^{(n)} - E_t(y_{t+1}^{(n)}) = B_n' \Sigma_F \omega_{t+1}$ and innovations to the log pd ratio are $pd_{t+1} - E_t(pd_{t+1}) = B_s' \Sigma_F \omega_{t+1}$.

The signs of the coefficients B_n and B_s determine the direction in which shocks to state variables ω_t move yield changes and stock returns.[5] The effects are particularly transparent if the Φ_F matrix is diagonal and after we impose additional restrictions on the short-rate coefficients δ_1. We motivate these restriction by theory and empirical estimates in more detail below. If $0 < \delta_g < 1$, then $B_s^g > 0$ and $B_n^g > 0$, i.e., growth news moves stocks and yields (bonds) in the same (opposite) direction. With $\delta_m = 1$, $B_s^m < 0$ and $B_n^m > 0$, i.e., monetary news moves stocks and yields (bonds) in opposite (the same) direction. Thus, while bonds hedge growth risk in stocks, both stocks and bonds are similarly exposed to discount rate changes induced by monetary shocks. Finally, $\delta_\tau = 1$ implies that expected inflation news affect yields positively $B_n^\tau > 0$, but has no effect on stocks ($B_s^\tau = 0$). Instead, $\delta_\tau > 1$ (the so-called Taylor principle) implies $B_s^\tau < 0$ and $B_n^\tau > 0$; as such, the impact of expected inflation shocks on stocks and yields is of opposite direction, and same as that of monetary shocks.

As one can view a stock as a long-term bond plus cash-flow risk, it is plausible that time-varying risk premiums on stocks and bonds are not perfectly correlated. At a basic level, one can think of two sources of risk-premium variation: (i) a common variation in compensation required by stock and bond investors due to both being exposed to interest rate risk; and (ii) a variation in the cash-flow risk premium that increases the risk premium on stocks but lowers the risk premium on bonds as bonds provide a hedge for bad economic times (as in "flight-to-safely" episodes). The model above allows to generate such structure in risk premiums. Suppose that shocks to g_t and m_t are priced with time-varying market prices of risk, while other shocks are priced with constant risk premiums. Then, shocks to the log

[5] Shocks ω_t affect the innovations to the log pd ratio and innovations to stock returns in the same direction, as the log-linearized return is $r_{t+1}^s \approx \kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t$.

SDF are[6]

$$\ln M_{t+1} - E_t(\ln M_{t+1}) = -\lambda_0' \Sigma_F^{-1} \omega_{t+1} - \frac{\lambda_{gx^+}}{\sigma_g} x_t^+ \omega_{t+1}^g - \frac{\lambda_{mx^-}}{\sigma_m} x_t^- \omega_{t+1}^m, \tag{10}$$

and risk premiums on stocks and bonds move on two factors. Denoting the one-period log excess returns as $rx_{t+1}^{(n)}$ for bonds and rx_{t+1}^s for stocks, the risk premiums are

$$E_t(rx_{t+1}^{(n)}) + \frac{1}{2} Var_t(rx_{t+1}^{(n)}) = \text{const.} \underbrace{-(n-1)B_{n-1}^g}_{(-)} \lambda_{gx^+} x_t^+ \underbrace{-(n-1)B_{n-1}^m}_{(-)} \lambda_{mx^-} x_t^- \tag{11}$$

$$E_t(rx_{t+1}^s) + \frac{1}{2} Var_t(rx_{t+1}^s) = \text{const.} + \kappa_1 (\underbrace{B_s^g}_{(+)} \lambda_{gx^+} x_t^+ + \underbrace{B_s^m}_{(-)} \lambda_{mx^-} x_t^-), \tag{12}$$

where κ_1 is a positive linearization constant slightly below unity. Thus, risk premiums inherit the exposures of stocks and bonds to g_t and m_t shocks via loadings B^g and B^m. Recall that bond prices and yields move in opposite direction. Because both stock and bond prices load onto m_t shocks with the same sign, shocks to x_t^- move bond and stock risk premiums in the same direction (generating a negative stock-yield comovement). Thus, the x_t^- variable represents the *common* risk premium variation in stocks and bonds. In contrast, because stocks and bonds load on growth shocks g_t with opposite signs, shocks to x_t^+ move bond and stock risk premiums in opposite directions (generating a positive stock-yield comovement). As such, the x_t^+ captures the variation in the *hedging* premium on bonds vis-a-vis stocks. In practice, we identify the signs of λ_{gx^+} and λ_{mx^-} jointly with x_t^+ and x_t^-. Therefore, in our empirical approach, we assume $\lambda_{gx^+} > 0$ and $\lambda_{mx^-} < 0$ such that positive shocks to x_t^+ and x_t^- both increase risk premiums in stocks. We thus denote $p_t^+ = \lambda_{gx^+} x_t^+$ and $p_t^- = \lambda_{mx^-} x_t^-$.[7]

In addition to the comovement between stocks and yields, the setting illustrates how structural shocks propagate in the cross-section of yield maturities through B_n for different n. Under the expectations hypothesis (EH), the effect of (any mean-reverting) shock to the short-rate should fade at long maturities. Indeed, under the EH, the long-term yield is the

[6] The specification in equation (10) implies that Λ_1 has two non-zero elements $\Lambda_{1(2,4)} = \lambda_{gx^+}$ and $\Lambda_{1(3,5)} = \lambda_{mx^-}$

[7] Such two-factor structure in risk premiums can be rationalized with the consumption-based model of Bansal and Shaliastovich (2013) as arising from the variation in the real and nominal uncertainties. Those two sources of uncertainty have opposite impact on the yield curve, but the same effect on stocks. Nominal (real) uncertainty raises (lowers) the Treasury premium; both uncertainties increase the equity risk premium. The mechanism lies in a combination of recursive utility with inflation expectations having real effects on growth (higher inflation predicting lower growth).

average of expected future short rates, $y_t^{(n),EH} = \frac{1}{n} E_t \left(\sum_{k=0}^{n-1} i_{t+k} \right)$. For illustration, let us assume that the short rate follows an AR(1) process $i_{t+1} = \rho_0 + \rho i_t + \epsilon_{t+1}$. Then, the long-term yield under EH is $y_t^{(n),EH} = \text{const.} + \frac{1}{n} \frac{1-\rho^n}{1-\rho} i_t$. If $|\rho| < 1$, the impact of shocks to the short rate declines with maturity n, as the loading is $\frac{1}{n} \frac{1-\rho^n}{1-\rho} < 1$ and it declines with n. In practice, as in the model above, the short-rate dynamics are more complex than the AR(1) example, but the intuition extends to the multivatiate case (see Internet Appendix B). Non-standard expectations formation (e.g., expectations stickiness) can generate non-monotonic responses of yields to short-rate shocks across maturities; still, as long as the short rate is stationary, its effect would eventually die out. Without shocks to the risk premium, it is therefore hard to explain why some news moves long-term yields more than short-term yields.

III. Recovering economic shocks from Treasury yields and the stock market

Our empirical approach begins with the reduced-form dynamics of asset prices (2), which combined with the pricing equation (1) imply the evolution of the state variables. We do not directly estimate the dynamics of the state variables, which are not observable, but rather we back them out from the reduced-form parameters of asset price dynamics and restrictions on the $\tilde{A}$ matrix. Consequently, shocks that we identify are innovations to the information set of investors.[8]

We impose intuitive and economically motivated sign restrictions on the responses of asset prices to shocks. This approach leads to a set (as opposed to a point) identification of $\tilde{A}$, and has both advantages and costs. Being more agnostic about the detailed structure of the economy, it is also less precise and rigorous. At the same time, it allows us to assess whether restrictions that are consistent with asset pricing models hold in the data and, if so, how informative they are.

Finally, as we recover ω_t at the daily frequency and over a long sample period, our analysis is not limited to times at which particular macroeconomic or monetary policy announcements occur and that likely represent only a subset of events when investors update expectations. In this way, we can measure the overall asset price impact of structural shocks we are interested in. To verify our approach, in Section VI, we also study whether shocks that we identify

[8]We focus on how investors interpret news events. For example, an employment announcement may cause investors to update their expectations about the state of the economy, but can also move expectations about monetary policy and/or change perceptions of risk (Boyd et al., 2005; Law et al., 2018). Our approach separates such information bundle into different components.

are consistent with macroeconomic shocks obtained with alternative identification schemes (e.g., the event study approach).

III.A. Restrictions

We want to recover four structural shocks in ω_t from a joint variation in the aggregate stock market and the Treasury yield curve, with $\omega_t = \left(\omega_t^g, \omega_t^m, \omega_t^{p+}, \omega_t^{p-}\right)'$ respectively denoting shocks to investor growth expectations (ω_t^g), shocks to expectations of monetary policy (ω_t^m), and two pure risk-premium shocks (ω_t^{p+}, ω_t^{p-}).

We focus on two dimensions of asset price response to a shock: the direction of the stock market response vis-a-vis the yield curve response, and the effect on the cross-section of yields across maturities. We use notation $\mathcal{R}^z$ to indicate the set of restrictions that identify shock z.

Restrictions on shocks to growth expectations, $\mathcal{R}^g$: *Positive shocks to growth expectations raise stocks prices and bond yields, and impact yields at short-to-intermediate maturities more than at long maturities.*

Growth news can affect stock prices (price-dividend/-consumption ratios) through the cash-flow news channel and through the discount-rate channel. Whether positive growth news raises or lowers stock prices depends on the relative strength of the two channels. In consumption-based asset pricing models such as the long-run risk, positive growth news raises stock prices when the intertemporal substitution effect dominates the wealth effect, i.e., the EIS is greater than one (e.g., Bansal and Yaron, 2004). In a model with a forward-looking Taylor rule presented in Section II.B, the cash-flow news effect dominates if the Fed tightens the real rate less than one-for-one with growth expectations ($0 < \delta_g < 1$). Those models predict that growth shocks move stocks and yields in the same direction. Importantly for identification purposes, in the cross-section of yields, we expect the effect to be more pronounced at short-to-intermediate maturities than at long maturities, reflecting the fact that growth shocks are mean-reverting (albeit can be persistent). This maturity pattern is documented by a number of empirical studies (Balduzzi et al., 2001; Fleming and Remolona, 2001; Gürkaynak et al., 2005b, 2018).[9]

[9] The results in Balduzzi et al. (2001) are reported for bond returns (rather than yield changes) and need to be divided by the negative of duration to be comparable with other studies. The effect of real activity news on the yield curve is typically found to be hump-shaped, declining between two-to-three-year segment through the long-maturity segment. The hump shape is consistent with models that have backward-looking

To further motivate the $\mathcal{R}^g$ restrictions, we provide evidence based on updates of expectations about the real GDP (RGDP) growth from the Blue Chip Economic Indicators (BCEI) survey, available monthly. Survey updates proxy for innovations in forecasters' beliefs about economic growth (e.g., Romer and Romer, 2004).[10] In Table I, we regress monthly S&P 500 index returns and zero-coupon yield changes over the 1983–2017 sample on contemporaneous RGDP growth forecast updates, controlling for simultaneous updates of CPI inflation forecasts.[11] For stock returns (column (1)), the coefficient on the RGDP update one quarter ahead is positive, implying that a 1% upward revision of growth expected next quarter is associated with 5.8% higher stock returns in a given month ($t = 3.6$). For yields, a 1% growth update raises two-year yield (column (3)) by 25 bps ($t = 4.13$) and the ten-year yield by only 7.5 bps ($t = 1.1$), with the difference between the coefficients significant at the 1% level (column (8)). Hence, the declining effect of growth news across maturities is clearly visible. Expected inflation shocks do not have a significant contemporaneous effect on stocks, while their effect on the yield curve is flat across maturities, in line with the literature (Kozicki and Tinsley (2001), Rudebusch and Wu (2008), Cieslak and Povala (2015)).

Restrictions on monetary shocks, $\mathcal{R}^m$: *A monetary tightening shock depresses stocks prices and raises yields. The effect on yields declines in strength with yield maturity.*

The $\mathcal{R}^m$ restriction is supported by the findings of Rigobon and Sack (2004) that a surprise increase in short-term interest rate leads to a decline in stock prices and to an upward shift in the yield curve that becomes smaller at longer maturities. The reaction reflects the discount rate effect: a drop in the risk-free component of the discount rate pushes up stock and bond prices up on impact. In the cross-section of yields, the response of the two-year yield is typically estimated to be about two-to-three times as large as the response of the ten-year

components, e.g., as generated by sticky expectations where agents do not update their beliefs immediately, but they do eventually. In our empirical application, we do not take a stance on the hump shape, but we do require that growth news affect the ten-year yield less than the two-year and five-year yields, in line with the empirical evidence.

[10] We define the forecast update at a specific horizon h as the change between survey forecasts in two consecutive months (month $t-1$ and t) of the RGDP growth rate for the same calendar quarter in the future h, i.e., $\text{Updt}_t(g_h) = F_t(g_h) - F_{t-1}(g_h)$. With the available data, we can construct updates for the current quarter ($h = 0$) as well as one ($h = 1$), two ($h = 2$), and three ($h = 3$) quarters ahead. For example, an update observed in January 2000 (time t) for the current quarter ($h = 0$), $\text{Updt}_t(g_0)$, is the change between the January 2000 and December 1999 surveys in the forecast of the RGDP growth rate in the first quarter of 2000.

[11] Section III.C describes our data sources in more detail.

	(1) Δs_t	(2) $\Delta y_t^{(1)}$	(3) $\Delta y_t^{(2)}$	(4) $\Delta y_t^{(3)}$	(5) $\Delta y_t^{(5)}$	(6) $\Delta y_t^{(7)}$	(7) $\Delta y_t^{(10)}$	(8) $\Delta(y^{(2)} - y^{(10)})$
RGDP updt $h = 1$	5.80***	0.26***	0.25***	0.23***	0.18***	0.13**	0.075	0.17***
	(3.59)	(4.07)	(4.13)	(3.94)	(3.03)	(2.01)	(1.06)	(2.88)
CPI updt $h = 3$	0.15	0.59***	0.66***	0.66***	0.65***	0.62***	0.59***	0.068
	(0.05)	(2.98)	(3.29)	(3.31)	(3.20)	(3.09)	(2.96)	(0.60)
R^2	0.12	0.13	0.11	0.097	0.074	0.059	0.045	0.065
N	417	417	417	417	417	417	417	417

Table I. Effects of macroeconomic expectations updates on stocks and yields. The table presents regressions of monthly stock returns (column(1)) and yield changes (columns (2)–(7)) on updates to private sector expectations of real GDP growth and CPI inflation. Column (8) tests the difference between the coefficients in columns (2) and (7), by regressing the changes in the spread between the two- and ten-year yield on the expectations updates. The horizon for the expectations update is next quarter ($h = 1$) for the real GDP and three-quarters ahead ($h = 3$) for CPI inflation. The horizon of the RGDP forecast is chosen based on Bayesian information criterion (BIC) for the stock regression, the horizon of the CPI forecast is chosen based on the average BIC across yields. Yield coefficients on RGDP update have a similar monotonicity pattern for current quarter forecast (nowcast, $h = 0$), and become generally insignificant at longer horizons. Dependent and explanatory variables are in percentages. Regressions are estimated with a constant, which is not displayed in the table. The sample period is 1983–2017. Robust t-statistics are reported in parentheses.

yield.[12] While there is a debate as to how persistent monetary shocks are, the fact that they subside with maturity holds across different samples and methodologies (see Appendix Table IA-1 for a review of the related literature). Indeed, in macro models, conventional monetary shocks operate by affecting the real rate gap, i.e., the distance of the real federal funds rate from the equilibrium (or natural) real rate. As the gap mean-reverts, the effect of such shocks on yields declines with maturity.

We isolate two additional shocks to market prices of risk. These are shocks to financial assets that are orthogonal to monetary and growth news. Although we are agnostic about the exact mechanism, in asset pricing models risk-premium shocks arise from shifts in the (effective) risk aversion, sentiment or risk appetite more broadly (e.g., Lettau and Wachter, 2007, 2011), or from shocks to macroeconomic uncertainty (e.g., Bansal and Shaliastovich, 2013). As we show empirically, the two-factor structure in risk premium is key for jointly explaining the variation in stocks and the yield curve.

Risk-premium shocks, $\mathcal{R}^{p+}$ and $\mathcal{R}^{p-}$. *Risk-premium shocks move the longer-end of the yield curve more than the short end. The two shocks differ in the direction of the comovement between stocks and yields that they generate. We denote restrictions on risk-premium shocks*

[12] See Poole et al. (2002), Gürkaynak et al. (2005a), Gürkaynak et al. (2005b), Campbell et al. (2012), Hanson and Stein (2015), Nakamura and Steinsson (2018).

that induce a positive comovement between yields and stocks as $\mathcal{R}^{p+}$ and those that induce a negative comovement as $\mathcal{R}^{p-}$.

The assumption that risk-premium shocks move long-term yields more than short-term yields is further supported by both empirical and theoretical results in the literature (see e.g., Bansal and Shaliastovich (2013), Greenwood and Vayanos (2010), Hanson and Stein (2015), Cieslak and Povala (2015, 2016), Duffee (2016)).[13] Cieslak and Povala (2015) document that the effect of shocks to real-rate expectations declines in maturity while that of risk-premium shocks increases in maturity. They additionally show that the variation in bond risk premium is unconditionally uncorrelated with the expectations of the real-rate and of inflation. Duffee (2016) reports similar cross-sectional effects based on several different specifications of a reduced-form VAR model.[14] The estimates in this literature suggest that a one-standard deviation risk-premium shock moves the ten-year yield more than twice as much as the two-year yield.

None of the restrictions above isolates shocks to expected inflation. Expected inflation shocks have a level-effect on the yield curve (leaving its slope essentially unchanged) and an insignificant effect on the stock market, as indicated by Table I. While we leave inflation shocks unspecified, leading to a potential misspecification, we expect them to have a small effect on our results. The main reason is that inflation expectations are highly persistent with a very low conditional volatility, a consequence of investors updating their inflation expectations sluggishly over time (e.g., Sargent, 1999). As such, and despite expected inflation being the main determinant of the unconditional variation in the level of interest rates, its contribution to the high-frequency (daily in our application) variation in yields is small (Bekaert et al., 2010a; Cieslak and Povala, 2015). Duffee (2016) estimates that expected inflation news explains between 10% and 20% of quarterly variation in yields. This number is between 4% and 6% if we project monthly changes in yields on monthly CPI expectations updates (not reported separately in Table I). Extrapolating from these results suggests that

[13]Greenwood and Vayanos (2010) propose a model with risk-averse arbitrageurs, in which bond supply shocks drive bond term premiums. They show theoretically that supply shocks can either have a humped or increasing effect on yields across maturities. In their empirical application, however, they find that the effect of supply shocks on the cross section of yields increases with maturity.

[14]To the extent that real-rate shocks reflect a combination of growth and monetary news, the evidence in Cieslak and Povala (2015) and Duffee (2016) is in line with restrictions $\mathcal{R}^{g}$ and $\mathcal{R}^{m}$.

shocks to expected inflation should have a minimal impact on day-to-day variation in asset prices, which is the frequency we focus on.[15]

III.B. Summary of identification restrictions

Let $Y_t = (y_t^{(2)}, y_t^{(5)}, y_t^{(10)}, pd_t)$, where yield maturities n are expressed in years. Given $Y_t - E_{t-1}(Y_t) = \tilde{A}\omega_t$, we want to recover $\omega_t = (\omega_t^g, \omega_t^m, \omega_t^{p+}, \omega_t^{p-})'$ from innovations in Y_t by identifying $\tilde{A}$. The matrix of instantaneous responses of asset prices to structural shocks, $\tilde{A} = A\Sigma_F$, written out explicitly is

$$\tilde{A} = \begin{pmatrix} A_g^{(2)} & A_m^{(2)} & A_{p+}^{(2)} & A_{p-}^{(2)} \\ A_g^{(5)} & A_m^{(5)} & A_{p+}^{(5)} & A_{p-}^{(5)} \\ A_g^{(10)} & A_m^{(10)} & A_{p+}^{(10)} & A_{p-}^{(10)} \\ A_g^{s} & A_m^{s} & A_{p+}^{s} & A_{p-}^{s} \end{pmatrix} \begin{pmatrix} \sigma_g & 0 & 0 & 0 \\ 0 & \sigma_m & 0 & 0 \\ 0 & 0 & \sigma_{p+} & 0 \\ 0 & 0 & 0 & \sigma_{p-} \end{pmatrix}, \tag{13}$$

Superscripts (2), (5), and (10) refer to yield maturity, superscript s refers to the stock market response, and subscripts label the structural shocks. Moving across columns of $\tilde{A}$ describes how an asset responds to different shocks; moving across rows describes how a shock affects different assets. We impose three types of restrictions, all on the contemporaneous impact of structural shocks on innovations in asset prices: (i) *sign restrictions* that determine the direction in which a shock moves innovations to yields and stocks; (ii) *between-asset restrictions* that determine the relative effect of shock ω_i on the different elements of Y_t; and (iii) *within-asset restrictions* that determine the relative importance of different shocks on an element Y_i. Between-asset restrictions mean that Y_k responds more strongly than Y_m, $k \neq m$, to shock ω_i. The within-asset restrictions mean that Y_k responds more strongly to shock ω_i than to shock ω_j, $i \neq j$.

[15] In the model in Section II.B, expected inflation does not have a large effect on stocks if δ_τ is close to unity and $\Phi_{F(2,1)}$ is close to zero (i.e., τ_t does not effect g_t through the drift). Indeed, estimating a VAR using survey expectations for RGDP growth and CPI inflation over the post-1983 sample, we find that the feedback of expected inflation on expected growth is not statistically different from zero. The model also shows that (with $\delta_\tau > 1$) expected inflation shocks affect the comovement of stocks and yields in the same way as do monetary shocks. Assuming that x_t^- drives the variation in risk compensation for both expected inflation shocks (akin to the nominal uncertainty channel in Bansal and Shaliastovich (2013)) and monetary shocks does not change the implications for the stock-yield comovement. This implies that, by not identifying shocks to expected inflation, we could confound monetary shocks with expected inflation shocks. However, the empirical evidence summarized above suggests that the expected inflation shocks have a minor effect on daily changes in asset prices, and hence, the overwhelming part of variation in the identified ω_t^m shocks stems from monetary news.

Using the $+/-$ signs to denote the direction of an impact of a positive shock ($\omega_i > 0$), we assume that

$$\tilde{A} = \begin{pmatrix} + & + & - & + \\ + & + & - & + \\ + & + & - & + \\ + & - & - & - \end{pmatrix}. \tag{14}$$

Those sign restrictions mean that shocks ω^g and ω^{p+} move stocks and yields in the same direction (first and third column of $\tilde{A}$), whereas shocks ω^m and ω^{p-} move stocks and yields in opposite directions (second and fourth column of $\tilde{A}$). It is clear that sign restrictions themselves do not allow to distinguish ω^g from ω^{p+} and ω^m from ω^{p-}. This separation is achieved by imposing additional conditions on how shocks propagate along the maturity dimension of the yield curve.

The between-yield restrictions involve yields across different maturities and are imposed on elements of a column j of $\tilde{A}$, $\tilde{A}(:,j)$. We assume that growth and monetary shocks ω^g and ω^m drive the short end of the yield curve more than the long end of the yield curve, while the opposite holds for shocks driving the risk premiums, ω^{p+} and ω^{p-}. For the monetary shock, we have $A_m^{(2)} > A_m^{(5)} > A_m^{(10)}$. For risk-premium shocks, we flip the inequality sign. For growth shocks, we require that $A_g^{(2)} > A_g^{(10)}$ and $A_g^{(5)} > A_g^{(10)}$, but we do not constrain the relationship between $A_g^{(2)}$ and $A_g^{(5)}$ based on the evidence that growth news can exert a non-monotonic effect at short and intermediate maturities.

The within-yield restrictions constrain the relative contributions of different shocks to conditional volatilities of yields. These are constraints on the elements of a given row i of $\tilde{A}$, $\tilde{A}(i,:)$. Specifically, we assume that the conditional variance of the ten-year yield is to a larger extent determined by the risk-premium shocks than it is by shocks to short-rate expectations—growth and monetary shocks—and conversely for the two-year yield, i.e., $\frac{(A_m^{(2)}\sigma_m)^2+(A_g^{(2)}\sigma_g)^2}{(A_{p^+}^{(2)}\sigma_{p^+})^2+(A_{p^-}^{(2)}\sigma_{p^-})^2} > 1$ for the two year yield and $\frac{(A_m^{(10)}\sigma_m)^2+(A_g^{(10)}\sigma_g)^2}{(A_{p^+}^{(2)}\sigma_{p^+})^2+(A_{p^-}^{(2)}\sigma_{p^-})^2} < 1$ for the ten-year yield. Those restrictions are consistent with the evidence on the properties of interest rate volatility in Cieslak and Povala (2016).

III.C. Data description

Our main analysis uses daily data on zero-coupon nominal Treasury yields and the stock market index. Daily nominal zero-coupon yields are from Gürkaynak et al. (2006) published on the Federal Reserve Board website. Stock market returns on the S&P500 index are from WRDS. The main sample covers the period from 1983 to 2017. Whenever we present monthly or quarterly results, we use asset prices on the last day of a month/quarter, unless otherwise stated.

III.D. Estimation approach

We obtain reduced-form innovations to Y_t from a VAR(1) estimated on daily yield changes and daily stock returns, $z_t = \Delta Y_t = Y_t - Y_{t-1}$ over the sample from 1983 to 2017. We apply maximum likelihood on demeaned z_t. The lag length of one is determined using the Bayesian information criterion. In the context of the discussion in Section II.A, the estimation of VAR(1) in changes involves some approximations. First, we use log stock returns as opposed to changes of the log price-dividend ratio. Using Campbell-Shiller linearization with constants κ_0, κ_1, the log stock returns are $r^s_{t+1} \approx \kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t$ and return innovations are $r^s_{t+1} - E_t(r^s_{t+1}) \approx \kappa_1(pd_{t+1} - E_t(pd_{t+1})) + (d_{t+1} - E_t(d_{t+1}))$. The first term, $(pd_{t+1} - E_t(pd_{t+1}))$, captures shocks to the state variables we are interested in, while $(d_{t+1} - E_t(d_{t+1}))$ captures shocks to the current realizations of log dividends. At the daily frequency, however, the noise stemming from the second term can be assumed negligible given the smooth dynamics of aggregate dividends.[16] Second, as long as the VAR in changes is correctly specified, it holds that $u_t = Y_t - E_{t-1}(Y_t) = \Delta Y_t - E_{t-1}(\Delta Y_t)$. Using VAR(1) in changes implies a non-stationary dynamics of Y_t. While it is hard to argue theoretically that yields and price-dividend ratios have unit root, VAR(1) in changes is a convenient way of dealing with highly persistent dynamics in available data samples.

To recover structural shocks ω_t, we start from the Cholesky decomposition of the variance-covariance matrix of reduced-form shocks u_t, $\Sigma_u = PP'$, where P is a lower triangular matrix, $u_t = P\omega^*_t$, and ω^*_t denotes a set of uncorrelated shocks, $Var(w^*_t) = I$. Shocks w^*_t correspond to the recursive identification. In our application to asset prices, those shocks do not have an economic interpretation as it is hard to defend any particular ordering of asset prices in

[16] As a rough measure of the effect of current dividend shocks, we regress the cum dividend returns on capital gains in the S&P 500 index at the daily frequency. The slope coefficient is 1.006, the intercept is -1 basis point and the $R^2 = 0.9989$.

a VAR. One can obtain observationally identical set of reduced-form shocks by finding an orthonormal (rotation) Q matrix such that $QQ' = Q'Q = I$,

$$u_t = PQ'Qw_t^* \tag{15}$$

where Qw_t^* is another candidate set of uncorrelated shocks corresponding to a given matrix Q. We generate rotation matrices Q using the Householder transformation proposed by Rubio-Ramirez et al. (2010) (see also Kilian and Lütkepohl (2017)). While there are many matrices Q leading to observationally equivalent shocks u_t, we are interested in the subset that satisfies the restrictions laid out in Section III.B. Denoting the set of rotation matrices for which $\tilde{A}(Q) = PQ'$ satisfies the restrictions as $\mathcal{R}$, for each $Q \in \mathcal{R}$ we have

$$u_t = \tilde{A}(Q)\omega_t(Q) \quad \text{and} \quad \omega_t(Q) = Q\omega_t^*, \tag{16}$$

where Cholesky decomposition corresponds to $Q = I$ and $\omega_t^* = \omega_t(I)$. We store 1000 valid matrices that satisfy $\mathcal{R}$ on which we base our subsequent analysis.

III.E. Dealing with model multiplicity

The identification approach using sign restrictions leads to model multiplicity, each model corresponding to different $\omega_t(Q)$. Summary statistics, such as mean or median of $\omega_t(Q)$ across different Q's, mix different model solutions and, as such, lack a structural interpretation. Therefore, for discussion of our main results, we follow the approach of Fry and Pagan (2005, 2011) of selecting the median target (MT) solution. This is the solution for which instantaneous asset price responses to structural shocks are the closest to the median response. For each solution i satisfying our restrictions, we denote the vector of instantaneous responses as $\theta_i = vec(\tilde{A}(Q_i))$. We then standardize each solution, θ_i, by subtracting the median and dividing by the standard deviation, both measured over the set of models that satisfy identification restrictions:

$$\theta^{MT} = \min_i \left[\frac{\theta_i - \text{median}(\theta_i)}{\text{std}(\theta_i)}\right]' \left[\frac{\theta_i - \text{median}(\theta_i)}{\text{std}(\theta_i)}\right]. \tag{17}$$

As pointed out by Fry and Pagan (2011), when median shocks are uncorrelated, shocks obtained from the MT solution are equal to the median of shocks across models.

III.F. Estimates across solutions and sample periods

To illustrate the dynamics of shocks over time, Figure 1 graphs their cumulative paths, superimposing the MT solution with the median, the 10th, and 90th percentiles of cumulative shocks across all retained models. The y-axis in the graph is in units of standard deviation as $Var(\omega_t) = I$ over the full sample. The median and MT solutions generate nearly perfectly overlapping paths. The 10th and 90th percentiles illustrate the uncertainty associated with the set identification that arises due to model multiplicity, as opposed to estimation uncertainty. Estimation uncertainty is negligible compared to the model uncertainty, and we relegate the discussion of its role to the Internet Appendix (see Appendix Figure IA-1).

To compare solutions, we study the correlations between shocks from the MT and the other retained models. Correlations of the median of shocks across solutions with the MT shocks exceed 0.985 for all of the four elements in ω_t (at a daily frequency and on a noncumulative basis). The median correlation coefficients of MT shocks with other solutions is above 0.91 and the mean is above 0.81 (see Appendix Figure IA-2). This suggests that different solutions have similar implications for the evolution of structural shocks over time. Indeed, we find that different solutions broadly agree in terms of economic implications.

With Gaussian shocks our model abstracts from the time-varying second moments in asset prices. This fact may be concerning in view of the evidence that the correlation between stocks and yields changed sign from negative to positive in the late 1990s, and given that our sample encompasses the zero lower bound period, which constrained the volatility at the short-end of the yield curve. To examine whether these facts distort our identification, we reestimate the model on two subsamples, starting in the late 1990s (1998–2017 sample) and dropping observations that include the financial crisis and beyond (1983–2007 sample). A regression of shocks estimated over the subsamples on the full-sample estimates yields slope coefficients and R^2 close to one (coefficients range from 0.93 to 1.08 and R^2 all exceed 0.92). Detailed estimates are reported in Appendix Figure IA-3 and Appendix Table IA-2. Overall, the full and subsample results deliver consistent decompositions of asset prices into structural shocks.

In the next section, we apply the decomposition to study the drivers of stocks and yield over the FOMC cycle. We provide additional tests to validate of our identification in Section VI.

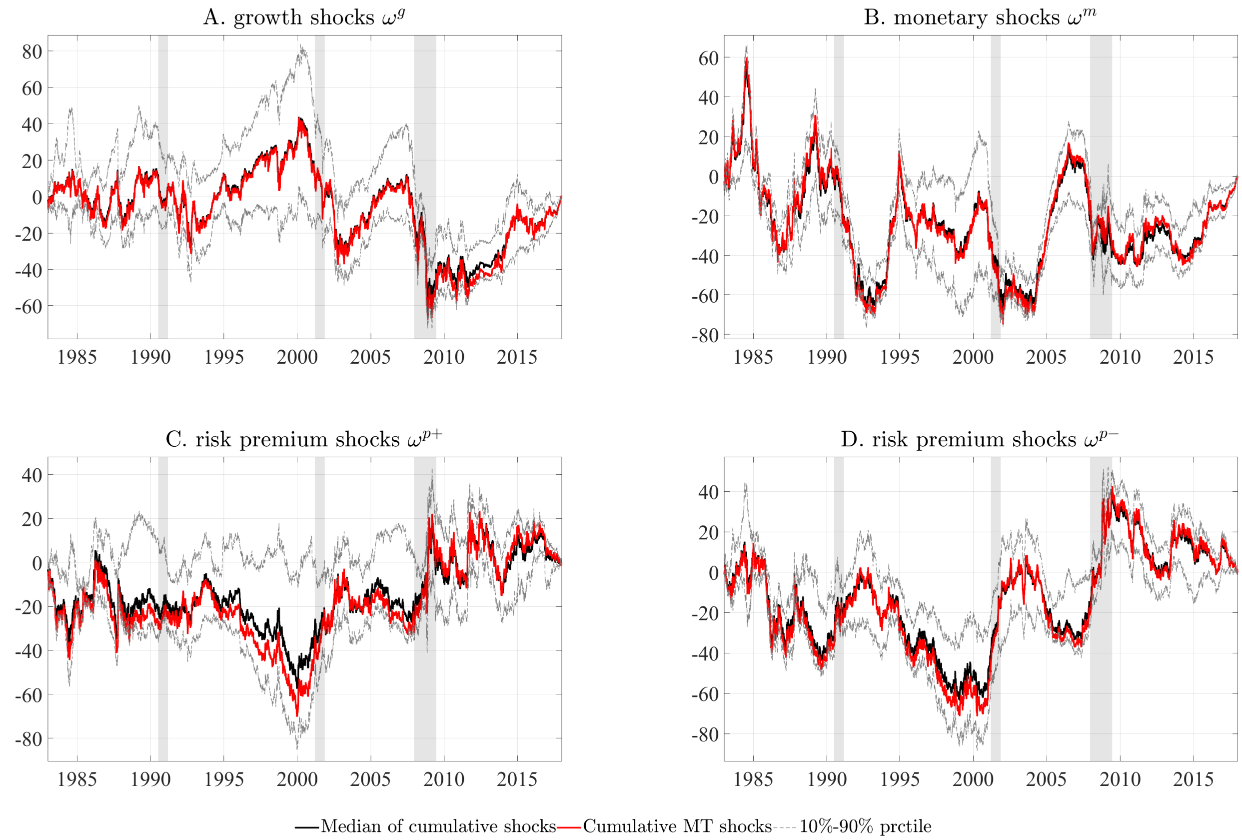

Figure 1. Paths of cumulative shocks. The figure presents paths of cumulative shocks for the MT solution as well as the median, 10th, and 90th percentile of cumulative shocks across retained solutions. Daily shocks are normalized to have zero mean and unit standard deviation over the 1983–2017 sample. Hence, cumulative shocks are expressed in units of standard deviations with paths starting and ending at zero.

IV. Stocks and Treasury yields on FOMC days and over the FOMC cycle

With the decomposition of asset prices into economic shocks, we study the asset price behavior on the day of FOMC meetings and over the full FOMC cycle, i.e. time between scheduled FOMC meetings. The current literature finds consistently positive stocks returns occurring at regular times during the FOMC cycle, but mixed and largely insignificant results for the Treasuries. This inconsistency between stocks and yields has been puzzling. We show that it can be explained by the opposing effects that different structural shocks have on yields.

For consistency with the literature, we begin this part of analysis in 1994. We use shocks estimated over the full 1983–2017 sample but the results are not materially changed if we re-estimate model starting in 1994.

IV.A. Historical decompositions of daily stock returns and yield changes

We can represent log stock returns or yield changes, i.e., each element of $z_t = \Delta Y_t$, as a sum of initial conditions z_1 and subsequent shocks:

$$z_t = \Phi_z^{t-1} z_1 + \sum_{k=0}^{t-2} \Phi_z^k \tilde{A} w_{t-k} \quad \text{for} \quad t > 1. \tag{18}$$

Let $z_t^j(\omega_t^i)$ denote the contribution of i-th shock, ω^i, to j-th element of z_t:

$$z_t^j(\omega_t^i) = \sum_{k=0}^{t-2} \Phi_z^k \tilde{A} J_{ii} w_{t-k}, \tag{19}$$

where J_{ii} is a square matrix with (i,i)-th element equal to one and zeros elsewhere. Equation (19) provides the historical decomposition of z_t. Summing up across shocks, $\sum_i z_t^j(\omega_t^i)$, we recover the overall stock return or yield change on day t (up to the initial condition).[17]

IV.B. FOMC days

We first revisit the evidence that stocks but not bonds earn large positive returns on days of scheduled FOMC meetings, as documented by Lucca and Moench (2015). In Table II, we regress overall log stock returns and yield changes as well as their historical decompositions (19) on the FOMC day dummy for scheduled announcements. All coefficients in the table are in basis points. By multiplying the coefficients for yield changes in Panel B and C by the negative of duration (two and ten years, respectively), one obtains the coefficients for bond returns (as $r_t^{b,(n)} = -n\Delta y_t^{(n)}$), whose magnitude can be compared with that for stock returns.

[17]The initial condition z_1 has a very small effect that dies out very quickly because daily stock returns and yield changes are not highly autocorrelated. Since vector z_t is demeaned, the historical decompositions describe how much each shock pushes z_t away from the unconditional mean of zero. Demeaning plays little role in practice because the daily unconditional means are close to zero, 4.3 bps for stock returns and less than -0.1 bps for yield changes over the 1983–2017 period.

Column (1) of Table II reproduces the estimates in Lucca and Moench (2015) based on the 1994–2017 sample. Stock returns are significantly higher on FOMC days, on average by 27.5 bps ($t = 3.32$), than on other days.[18] Yield changes are not: Two- and ten-year yields on average decline by about half basis point (statistically insignificant).

Columns (2)–(5) of Table II decompose the coefficient from column (1) into contributions of individual shocks. The shock-specific regressions reveal the differences between stocks and yields. While all shocks contribute positively to stock returns, their effect on yields is mixed. Focusing on Panel A, monetary shocks, ω^m, and two risk-premium shocks, ω^{p+} and ω^{p-}, unambiguously and significantly raise stock returns by 7, 9, and 9.7 bps, respectively. Turning to yields in Panels B and C, instead, monetary shocks and ω^{p-} shocks reduce the ten-year yield by -0.29 and -0.79 bps, respectively, while ω^{p+} shocks raise it by 0.52 bps. The combination of these opposing outcomes leads to insignificant yield changes overall.

The bulk of the above effects is due to monetary and risk-premium shocks, with the impact of growth shocks being insignificant. Nearly 70% (= 18.7/27.5) of the average increase in stock returns stems from ω^{p-}, ω^{p+} shocks (comparing columns (1) and (6) in Panel A). The positive sign means that FOMC days are associated with negative risk-premium shocks that push the stock prices higher.[19]

IV.C. FOMC cycle

The FOMC day returns are part of a broader pattern of stock returns between scheduled FOMC meetings. CMVJ (2019) show that excess stock returns are on average significantly higher in weeks zero, two, four and six in FOMC cycle time, i.e., in the even weeks starting from the last FOMC meeting. Their results are less clear for bonds.

In Table III, we re-estimate the baseline CMVJ regressions of stock returns and yield changes on even-week dummies separately for shock-specific components. The structure of the table is the same as Table II. Column (1) in Panel A reproduces the main empirical result in CMVJ showing that stock returns are on average 13.4 bps ($t = 3.09$) per day higher in week

[18] We present estimates for the sample used by Lucca and Moench (2015), from September 1, 1994 to March 30, 2011, in Appendix Table IA-8. Over this period, we find that stocks are 33 bps higher on FOMC days ($t = 3.29$) than on other days, which is the same estimate as obtained by Lucca and Moench (2015).

[19] Recall that in our identification positive risk-premium shocks lower stock prices (equation (14) and Figure 3). As we show in Section VI.C, those shocks comove positively with innovations to measures of equity risk premiums (Table VIII).

	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Of which due to shock:				
	A. Log stock returns (bps)					
	Δs	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
FOMC day dummy	27.5***	1.80	7.03*	9.03*	9.65*	18.7**
	(3.32)	(0.37)	(1.77)	(1.86)	(1.80)	(2.53)
Constant	-1.51	0.042	-0.67	-0.40	-0.49	-0.89
	(-1.01)	(0.06)	(-1.20)	(-0.48)	(-0.77)	(-0.85)
N	6053	6053	6053	6053	6053	6053
	B. Two-year yield changes (bps)					
	$\Delta y^{(2)}$	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
FOMC day dummy	-0.49	0.11	-0.56*	0.27*	-0.31**	-0.036
	(-1.05)	(0.38)	(-1.78)	(1.88)	(-1.97)	(-0.17)
Constant	0.062	0.0036	0.055	-0.012	0.015	0.0030
	(0.90)	(0.08)	(1.26)	(-0.50)	(0.84)	(0.10)
	C. Ten-year yield changes (bps)					
	$\Delta y^{(10)}$	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
FOMC day dummy	-0.49	0.063	-0.29*	0.52*	-0.79*	-0.27
	(-0.93)	(0.38)	(-1.78)	(1.88)	(-1.90)	(-0.54)
Constant	0.046	0.0021	0.029	-0.024	0.040	0.016
	(0.60)	(0.08)	(1.28)	(-0.50)	(0.81)	(0.23)

Table II. FOMC dummy regressions. The table reports regressions of daily yield changes and daily log stock returns on the FOMC day dummy for scheduled FOMC meetings. In column (1), the dependent variable is the overall return or yield change. In columns (2)–(5), the dependent variable is the historical decomposition (19) representing the part of the overall yield change (stock return) explained by a particular shock. Thus, regression coefficients across columns (2)–(5) sum up to the coefficients in column (1). Column (6) separately reports the regressions for the risk premium part. Regressions are estimated over the 1994–2017 sample, covering 192 scheduled FOMC meetings. Shocks are estimated over the 1983–2017 sample. All coefficients are in basis points. t-statistics robust to heteroskedasticity are reported in parentheses.

0 and 10.2 bps (t = 3.03) per day higher in weeks 2, 4, and 6 of FOMC cycle than they are in the other weeks.[20] Subsequent columns show that the result is largely driven by the risk-premium shocks ω_t^{p-} contributing 7.7 bps (t = 3.76) to week 0 and 4.3 bps (t = 3.02) to weeks 2, 4, and 6 stock returns. The estimates also suggest that the remainder of the overall effect is split among the other shocks. Growth news contribute 4.2 bps to stock returns in

[20]CVMJ estimate the respective coefficients to be 14.1 and 10.9 bps. Compared to CMVJ's main sample (1994–2016), we add one extra year of data. Note that the constant in column (1) is statistically significant at -5.9 bps, while in CMVJ it is not. This is because we demean daily stock returns before estimating the model. This does not affect the size of the coefficients on the even-week dummies.

week 0, while monetary and ω^{p-} shocks contribute 2 and 2.7 bps, respectively, in weeks 2, 4, and 6.

The overall results for yields in column (1) of Panels B and C are much weaker and marginally significant only in week 0 for the 10-year yield (-0.46 bps decline with $t = 2$). However, shock-specific regressions reveal a negative and significant impact of the ω^{p-} shocks across all even weeks, which parallels the estimates for stocks and implies a decrease in Treasury premiums. The negative coefficient for the week 2, 4, 6 dummy is reinforced by monetary shocks which push yields down (with marginal statistical significance) in those weeks, suggesting that more news about monetary easing comes out in even weeks in FOMC cycle time. This channel, however, is quantitatively only about a quarter of that of the ω^{p-} shocks.

Those findings concur with the interpretation in CMVJ that the Fed has been able to reduce risk premiums on risky assets, with the economic magnitude of the reduction in the risk premium being much larger than the effect of pure monetary shocks.

IV.D. Path shocks, information effects and risk premiums

The results so far help cast light on channels through which central banks affect asset prices, and long-term interest rates in particular. Two views in the literature emphasize the information channel and the risk-premium channel of central bank communication. In the information channel, the central bank reveals additional information about economic fundamentals that markets did not have; in the risk premium channel, it influences the amount or the price of risk perceived by investors. Importantly, those two views are not in conflict as both channels can exist simultaneously.

Next, we quantify the importance of those different channels in the context of central bank communication shocks. Gürkaynak et al. (2005a, GSS) show how to decompose Fed announcements into an actions and communication component, which they refer to as target and path shocks. Path shocks are defined as news about the future path of policy that is uncorrelated with current target shocks (i.e., with shocks to the current Fed's policy rate). In principle, however, path shocks could be a combination of monetary and non-monetary news. Campbell et al. (2012) and Nakamura and Steinsson (2018) argue that a large portion of path shocks is due to Fed telegraphing information about growth, i.e., the information channel. Hanson and Stein (2015) do not use path shock directly (and measure Fed shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Of which due to shock:				
		A. Log stock returns (bps)				
	Δs	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
Week 0 dummy	13.4***	4.23**	0.88	0.63	7.68***	8.31***
	(3.09)	(1.99)	(0.52)	(0.25)	(3.76)	(2.58)
Week 2, 4, 6 dummy	10.2***	1.29	2.04	2.66	4.25***	6.91***
	(3.03)	(0.82)	(1.64)	(1.45)	(3.02)	(2.97)
Constant	-5.89***	-0.96	-1.21*	-1.03	-2.69***	-3.72***
	(-3.03)	(-1.02)	(-1.65)	(-0.95)	(-3.25)	(-2.75)
N	6053	6053	6053	6053	6053	6053
		B. Two-year yield changes (bps)				
	$\Delta y^{(2)}$	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
Week 0 dummy	-0.030	0.26**	-0.075	0.021	-0.24***	-0.22**
	(-0.15)	(2.08)	(-0.56)	(0.27)	(-4.01)	(-2.25)
Week 2, 4, 6 dummy	-0.13	0.083	-0.16*	0.083	-0.13***	-0.049
	(-0.84)	(0.88)	(-1.67)	(1.50)	(-3.21)	(-0.72)
Constant	0.091	-0.060	0.10*	-0.032	0.083***	0.051
	(1.00)	(-1.05)	(1.72)	(-0.99)	(3.45)	(1.24)
		C. Ten-year yield changes (bps)				
	$\Delta y^{(10)}$	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
Week 0 dummy	-0.46**	0.15**	-0.039	0.040	-0.62***	-0.58***
	(-2.00)	(2.07)	(-0.58)	(0.28)	(-3.91)	(-2.67)
Week 2, 4, 6 dummy	-0.22	0.049	-0.084*	0.16	-0.34***	-0.18
	(-1.27)	(0.87)	(-1.68)	(1.51)	(-3.13)	(-1.20)
Constant	0.17*	-0.035	0.052*	-0.063	0.22***	0.15*
	(1.66)	(-1.05)	(1.75)	(-0.99)	(3.37)	(1.68)

Table III. FOMC cycle regressions. The table reports regressions of daily yield changes and daily log stock returns on the FOMC day dummy for scheduled FOMC meetings. In column (1), the dependent variable is the overall return or yield change. In columns (2)–(5), the dependent variable is the part of the overall variation due to each shock. Thus, slope and intercept coefficients across columns (2)–(5) sum up to the coefficients in column (1). Column (6) separately reports the regressions for the risk premium part. Regressions are estimated over the 1994–2017 sample, covering 192 scheduled FOMC meetings. Shocks are estimated over the 1983–2017 sample. All coefficients are in basis points, i.e. t-statistics robust to heteroskedasticity are reported in parentheses.

using changes in the two-year yield), but their interpretation is consisted with a large part of path shocks arising from the risk-premium channel.

To link our shocks to GSS, we use data from Swanson (2018) who updates the original GSS target and path shocks through October 2015 and extends the GSS methodology to include large scale asset purchases (LSAP) shocks. GSS/Swanson identification exploits movements in shortest maturity interest rates from Fed fund futures and Eurodollar contracts (as well as in some longer-term rates) within a 30-minute window around the Fed announcements. Our approach, instead, relies on daily changes in Treasury yields with maturities of two-year and above, and no event-timing restrictions.

In Table IV, we project each of target, path and LSAP shocks on $\omega^g, \omega^m, \omega^{p+}$, and ω^{p-}. Column (1) shows that monetary shock in our decomposition is the only variable that has explanatory power for GSS target shock. A one standard deviation increase in ω^m is associated with 0.4 standard deviations increase in the target shocks. In contrast, path shocks in column (2) are significantly related to all variables except ω^{p+}, implying that path shocks combine various channels through which Fed communication can affect asset prices. All significant loadings are positive, i.e., a negative path shock can occur because of negative fundamental information revealed by the Fed announcements, news about monetary easing, or news that reduces the risk premium. In terms of economic significance, the monetary component appears to be the largest contributor, followed by the premium ω^{p-} and growth shocks.

Those results help explain the finding of Gürkaynak et al. (2005a) that path shocks have no effect on stocks but a strongly significant effect on Treasury yields. Suppose we observe a negative path shock. All shocks (growth, monetary, and premium ω^{p-}) that path embeds move yields in the same direction (down). For stocks, however, the positive effect of monetary and premium news is at least partially offset by the negative effect of growth news, dampening the overall stock market response.

Given that post 2008 many Fed announcements involve unconventional policy moves, in column (3), we separately report results for the Swanson's LSAP shocks. The sample starts in 2009 when the Fed first launched quantitative easing. We normalize the LSAP shock so that its positive value implies interest rate increases, as in Swanson (2018). The estimates indicate sizeable risk premium effects, with ω^{p-} having a large and positive coefficient of 0.72 (in standard deviation units), which suggests a decline in the risk premium on both stocks and bonds. The significance of ω^{p-} is robust to omitting the most powerful announcement on March 18, 2009 (albeit the coefficient drops to 0.47, not reported in any table). The significance of ω^{p+} is instead entirely driven by this single event. Overall, these results agree with the interpretation that LSAP worked primarily through reducing the risk premiums on stocks and long-term bonds.

	(1)	(2)	(3)
	Target	Path	LSAP
ω^g	0.100	0.256***	0.108
	(1.01)	(2.84)	(0.88)
ω^m	0.396***	0.517***	0.027
	(3.83)	(6.53)	(0.17)
ω^{p+}	0.008	-0.064	-0.338**
	(0.11)	(-0.97)	(-2.22)
ω^{p-}	-0.011	0.352***	0.715***
	(-0.12)	(4.53)	(3.13)
R^2	0.18	0.46	0.68
N	175	175	55

Table IV. Link to target and path shocks. The table reports regressions of GSS/Swanson shocks on shocks obtained using our identification. In column (1) and (2) the sample runs from 1994 through October 2015 (175 scheduled FOMC meetings). In column (5) the sample starts in 2009 and ends in October 2015 (55 scheduled FOMC meetings). Regression coefficients are standardized. t-statistics robust to heteroskedasticity are reported in parentheses.

V. Shocks in stocks and yields since early 1980s

In this section, we analyze the amount of overall variation in yield changes and stock returns induced by each structural shock. We then turn to the impulse functions to explore the dynamic effects of those shocks.

V.A. Variance ratios

Variance ratios describe the fraction of an asset's variance attributed to a shock. We compute the variance ratios as

$$VR_d^{j,i} = \frac{Var(u_t^j|\omega_t^i)}{Var(u_t^j)}, \tag{20}$$

where u_t^j is the reduced-form innovation to an asset j, ω_t^i is the structural shock i, $Var(u_t^j|\omega_t^i)$ is the variance in reduced-form innovations induced by ω_t^i, and $Var(u_t^j)$ is the overall variance of asset's j innovations. Since ω_t shocks are orthogonal, we have $\sum_{i=1}^4 VR_d^{j,i} = 1$. In our setting the conditional variances of reduced-form and structural shocks are constant. However, in practice, the relative importance of different shocks can vary over time. While we do not estimate a fully-fledged model with stochastic volatility, to assess the degree of such variation, we construct the variance ratios for the full sample (1983–2017) and for three subsamples, 1983–1997, 1998–2007, and 2008–2017.[21] The split dates in 1997 and 2007 demarcate periods that are likely to represent different economic and monetary policy environments.

Figure 2 displays the decomposition of daily innovations in yield changes and stock returns into contributions of structural shocks.[22] In interpreting the graph, it is important to distinguish between assumptions and results. While our identification imposes within- and between-asset restrictions, it does not constrain the magnitude of the incremental effects. For example, the contribution of monetary shocks could decrease slowly or quickly with yield maturity; likewise, structural shocks could each have roughly the same or very different effects on a given asset. It is an empirical question, which of these patterns best characterizes the data.

Looking at yields first, about 80% of daily variance in two-year yield is due to monetary and growth news. At the same time, monetary and growth news explain only about 20% of daily variance in the ten-year yield, with the rest attributed to the risk-premium shocks. This pattern remains relatively stable when comparing the full- and sub-sample results. The decomposition of stock returns, instead, reveals significant variation across samples. The most visible change pertains to the ω^{p-} shocks, which explain nearly 50% of stock return variance in the pre-1998 sample, dropping to about 10% in the post-2007 sample. This shift is accompanied by an increased contribution of growth and ω^{p+} shocks. Given that ω^{p-} shocks induce a negative comovement of stocks and yields, while ω^{p+} and growth shocks induce a positive comovement, the shifts in the variance decompositions help clarify the change in the stock-yield comovement from negative to positive in the late 1990s. The contribution of monetary shocks for stock returns remains relatively low compared to other shocks; notably, its explanatory power for yields also declines over time.

V.B. Impulse responses

To study the dynamic effects of shocks on asset prices, we use the local projections approach of Jordà (2005) by regressing multihorizon yield changes and log stock returns on the vector

[21] Shocks estimated over those subsamples are very highly correlated with shocks estimated over the full sample (Appendix Figure IA-4).

[22] Figure 2 presents variance decompositions based on the MT solution. Average variance ratios across all retained solutions lead to similar conclusions and are reported in Appendix Figure IA-6. Additionally, Appendix Figure IA-6 quantifies the amount of uncertainty in these estimates stemming from set identification.

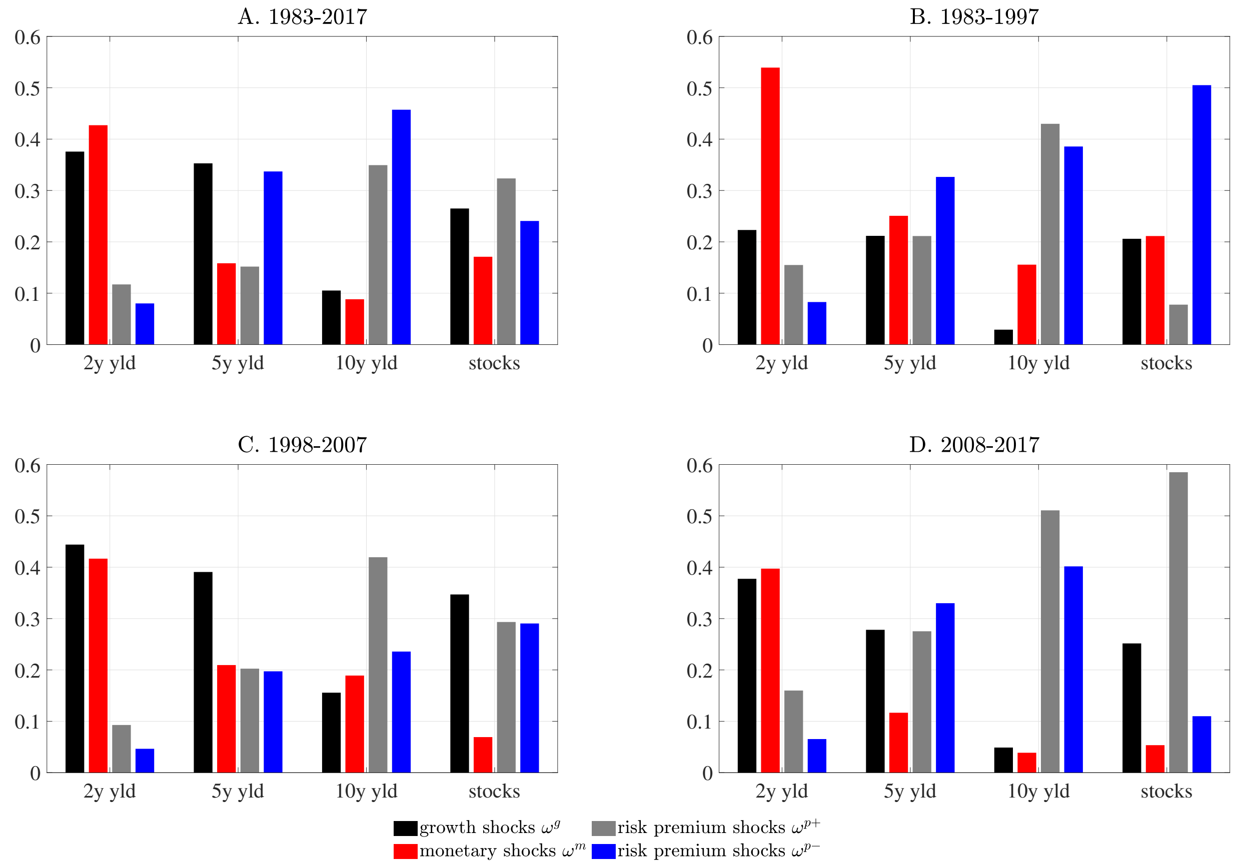

Figure 2. Variance decompositions. The figure presents variance decompositions of innovations in asset price into structural shocks. The structural shocks are obtained from the MT solution. The bars show the fraction of variance explained by each structural shock. Panel A reports full-sample estimates over the 1983–2017 period. Panels B through D are based on separate estimates for subsamples.

of structural shocks, ω_t:

$$Y^j_{t+h-1} - Y^j_{t-1} = \alpha_h + \beta^{j\prime}_h \omega_t + \varepsilon_t. \tag{21}$$

Horizon h is in business days. The coefficient $\beta^{j,i}_h$ measures the effect of a one-standard-deviation shock in ω^i_t on a h-day yield change or stock return. Our identification assumptions only restrict contemporaneous effects ($h = 0$), leaving the responses for $h > 0$ unconstrained. Tracing out $\beta^{j,i}_h$ as a function of h, we obtain the impulse-response functions.[23]

[23] The full specification of Jorda's controls for the level of Y_{t-1}, i.e., $Y^j_{t+h-1} - Y^j_{t-1} = \alpha_h + \beta^{j\prime}_h \omega_t + \delta'_h Y_{t-1} + \varepsilon_t$. Including those controls leads to almost identical results as (21); therefore, we report results of the more parsimonious version with $\delta_h = 0$. When $h = 0$, regression (21) delivers R^2 (essentially) equal to one as $h = 0$ corresponds to the contemporaneous decomposition of reduced-form shocks into structural shocks. The R^2 is exactly one when we include the lagged change in Y_t, consistent with the VAR specification used to obtained structural shocks.

In Figure 3, we plot the $\beta_h^{j,i}$ coefficients. The maximum horizon is 756 business days, corresponding roughly to three years. We compute the error bands with the Newey-West covariance matrix with $h+1$ lags, taking ω_t shocks as given; hence, the error bands do not reflect shocks' estimation uncertainty (which is negligible, see Appendix Figure IA-1) nor uncertainty stemming from the set identification.

Moving across rows of Figure 3, we see how a particular shocks impacts different assets. The on-impact responses (at $h = 0$) are displayed in the bottom left corner of each graph. Across all shocks, the dynamic effects have signs consistent with contemporaneous restrictions. Growth shocks generate persistent and positive responses in stocks and yields that mean-revert slowly with time. Monetary shocks drive yields up, more so at shorter maturities, and stocks down. The effect of a one-standard-deviation shock on the two-year yield is 3.6 basis points on impact[24] and increases up to 8 basis points at about two-year horizon. For assets other than the two-year yield, the effects of monetary shocks mean-revert within about a year. The risk-premium shocks ω_t^{p+} have persistent effect on all assets, while ω_t^{p-} shocks impact mostly the long-maturity yields and stocks. The effect of ω_t^{p-} on stocks accumulates over time to -1.16% up to a three-year horizon. The effect on the ten-year yield remains stable for about a year and becomes insignificant afterwards.

VI. Validity of identified shocks

This section studies the relationship between shocks identified with our scheme and alternative measures of those shocks outside of our model. Since shocks to investors' expectations are not directly observable, we draw on survey data, event study methodology, and estimates in the literature to provide a validity check for our approach.

VI.A. Growth news

Our external measure of growth news is based on the variation in forecast updates about the real GDP growth in the BCEI survey. To make model-based shocks comparable with

[24]This magnitude is in line with estimates based on Kuttner surprises. Using all (scheduled) meeting dates in Kuttner's sample (1989:06–2008:06), a one-standard deviation surprise leads to a 3.7 bps (2.9 bps) increase in the two-year yield. Our estimates are based on all dates, as opposed to only the FOMC meeting dates for which Kuttner's surprises are available.

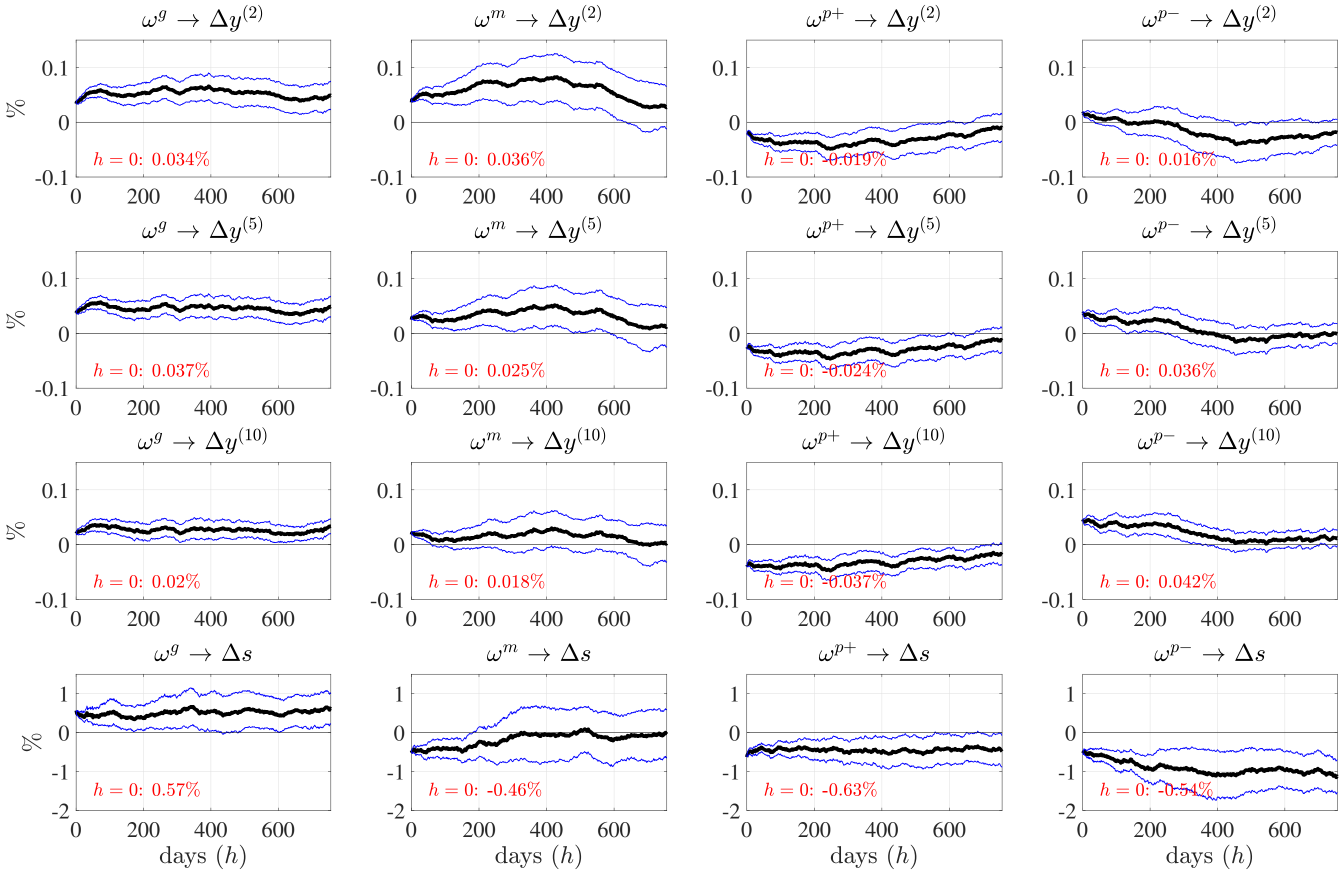

Figure 3. Impulse-response functions. The figure presents responses of yield changes and log stock returns to structural shocks. Shocks are measured in units of standard deviation. Yield changes and stock returns are in percent. The solid thick line traces out the coefficients $\beta_h^{j,i}$ from regression (21). A coefficient of 0.1 (1) implies an asset response of 0.1% (1%) to a one standard deviation shock. The thin lines mark the two-standard-error bands calculated with Newey-West adjustment using $h+1$ lags. The bottom left corner of each graph displays the coefficient on impact (i.e., for $h=0$). The sample period is 1983–2017.

the survey updates, we sum up the daily ω^g shocks over the last k months.[25] Similarly, for the survey, we cumulate monthly forecast updates over the same k-month period, for each survey horizon, h.

In Table V, we project model-based growth news over the last $k = 12$ months on the corresponding survey-based news.[26] Our identification assumes that growth news is driven by a single factor. Survey data, instead, suggest that growth updates across horizons are

[25] This approach is equivalent to calculating the change in the level of cumulative shocks (displayed in Figure 1) between the end of current month t and the end of month $t-k$.

[26] Appendix Table IA-3 contains results for $k = 3$ months, leading to similar conclusions.

driven by two main principal components (PCs), explaining respectively 76% and 21% of variation (for $k = 12$ months). It is therefore informative to explore how our shocks correlate with the survey updates at different forecast horizons. We report univariate horizon-specific regressions in columns (1) through (4) and regressions on four PCs of survey updates in column (5) of Table V. Survey updates explain up to 53% of variation in model-based growth news. The strongest correlation arises at the short survey horizons. Updates to the current quarter growth forecasts ($h = 0$) explain 45% of variation in model-based growth news with a standardized slope coefficient of 0.67 (t-statistic = 8.0, column (1)), while updates to growth forecasts at three quarters ahead ($h = 3$) explain less than 6% with a standardized slope coefficient of 0.24 (t-statistic = 1.1, column (4)). Comparing the univariate specification in column (1) to the four-PCs specification in column (5) shows an increase in the R^2 from 45% to 53%. As such, the single growth news factor in our model captures the main source of variation in the survey-based forecast updates. Figure 4 illustrates this fact by superimposing the growth shocks from the model against the survey data. The two series show close comovement across recessions and recoveries.

	(1) $h = 0$	(2) $h = 1$	(3) $h = 2$	(4) $h = 3$	(5) PCA
$\text{Updt}^{BC}(g_h)$	0.669***	0.672***	0.501***	0.242	
	(8.00)	(8.66)	(3.44)	(1.14)	
PC1					0.600***
					(9.05)
PC2					0.379***
					(7.11)
PC3					-0.160**
					(-2.58)
PC4					-0.003
					(-0.03)
R^2	0.45	0.45	0.25	0.059	0.53
N	408	408	408	408	408

Table V. Growth shocks. The table reports regressions of growth shocks obtained with our identification scheme as the dependent variable on contemporaneous real GDP growth expectations updates from the BCEI survey. Model shocks and survey updates are cumulated over the past $k = 12$ months and are sampled monthly. The regressions are estimated at the monthly frequency over the period 1983–2017. Slope coefficients are standardized with left- and right-hand side variables measured in z-scores. t-statistics in parentheses are Newey-West adjusted with 18 lags to account for overlapping data.

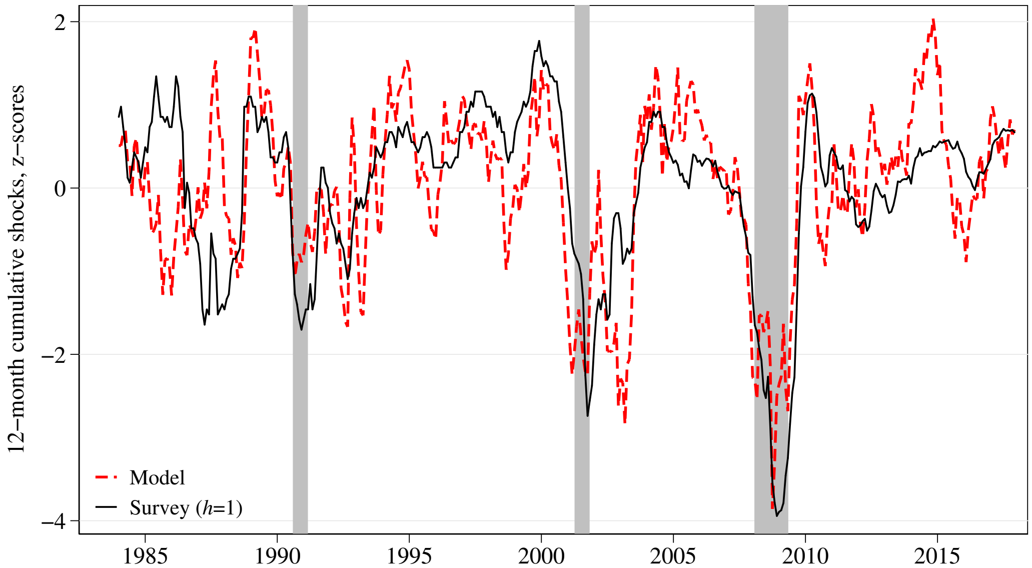

Figure 4. Time series of growth shocks and survey forecast updates for real GDP growth. The figure superimposes growth shocks with the forecast updates of real GDP growth expectations from the BCEI survey. The shocks and survey updates are cumulative over a 12-month period. Survey updates are for the current quarter ($h = 1$). Both variables are standardized to have a zero mean and unit standard deviation.

VI.B. Monetary shocks

If our identification assumptions are correct, we expect the variance of monetary shocks ω^m to be higher on days of key monetary announcements compared to other days. For this part of the analysis, we consider only scheduled FOMC meetings over the 1994–2008 sample to focus on days that are least likely to be contaminated by other types of news.[27]

In Panel A of Table VI, we regress absolute values of each shock on the FOMC dummy. The use of absolute values (as opposed to signed shocks) serves to quantify the amount of news that comes out on FOMC days relative to other days. Across the four shocks, the only significant slope coefficient is for monetary shocks (column (2)). The absolute magnitude of ω^m shocks is 36% higher ($= 0.27/0.75$) on FOMC days compared to other days and the difference is strongly significant (p-value of 0.1%). The volatility of other shocks is not

[27]We focus on scheduled meetings because unscheduled FOMC announcements are usually interpreted as Fed's response to other (unexpected) news events (e.g., Bernanke and Kuttner, 2005), and thus may not reflect monetary news alone. We start the sample when the Fed began making public announcements of their policy changes in 1994; before 1994, there remains uncertainty about the timing of when Fed decision reached financial markets (Thornton, 2005). We also omit the post-2008 period, when the Fed launched an array of unconventional policy measures that affected asset prices through multiple channels. We discuss these channels separately in the later part of the paper.

significantly different on FOMC days from other days. As a non-negligible portion of Fed communications happen outside of regularly scheduled FOMC meetings (and thus affect the regression intercept), the coefficient in column (2) is a conservative measure of the amount of monetary news on FOMC days.

Panel B of Table VI additionally presents regressions of signed shocks on the FOMC dummy. This regression allows to assess if the direction of news coming out on FOMC days is systematically different from other days. The FOMC dummy coefficient of -0.19 for ω^m in column (2) suggests that monetary shocks are 19% of standard deviation lower on FOMC days than they are on other days ($t = -1.53$). This result is consistent with the properties monetary policy surprises constructed by Kuttner (2001).[28] Similarly, the coefficient of -0.15 for the risk premium shock ω^{p-} in column (4) means that those shocks are on average 15% of standard deviation lower on FOMC days than on other days ($t = -1.73$). Indeed, Fed announcements can affect asset prices through channels other than pure monetary news, including risk premiums and information about economic fundamentals. We defer the discussion of the Fed announcement effect on other shocks to subsequent sections.

In sum, although we do not exploit information about the timing of FOMC announcements, our identification correctly detects an increase in the amount of monetary news on days when such news is likely to be prevalent.

VI.C. Risk-premium shocks

To assess the validity of our identification of risk-premium shocks, we rely on the estimates of bond and equity risk premium proposed in the literature. To measure the variation in the bond risk premium, we use the Cochrane and Piazzesi (2005, CP) factor and the cycle factor from Cieslak and Povala (2015) ($\widehat{cf}$). For the equity risk premium, we include measures from Lettau and Ludvigson (2001, CAY), Kelly and Pruitt (2013, KP), and forward equity premiums at several maturities from Martin (2017). These alternative measures are available at different sampling frequencies and over different sample periods. An increase in a given variable means an increase in the corresponding risk premium.

[28]Kuttner's surprises are available on Ken Kuttner's website up to June 2008, which we extend through the end of 2008. Similar to the shocks from our identification approach, over the 1994–2008 sample, Kuttner's surprises on scheduled FOMC meeting days are slightly negative, with an average of -0.75 bps ($t = -1.3$), compared to a standard deviation of 11 bps. Kuttner's surprises are estimated using the Fed fund futures contracts with the shortest maturity, while our estimation relies of information Treasury yields with maturities of two years and above.

	(1)	(2)	(3)	(4)
A. Regressions of absolute values of shocks on FOMC day dummy				
	$\lvert\omega^g\rvert$	$\lvert\omega^m\rvert$	$\lvert\omega^{p+}\rvert$	$\lvert\omega^{p-}\rvert$
FOMC day dummy	0.057	0.27***	-0.033	0.049
	(0.85)	(3.33)	(-0.73)	(0.82)
Constant	0.71***	0.75***	0.69***	0.67***
	(58.61)	(60.79)	(60.90)	(64.58)
N (days)	3784	3784	3784	3784
B. Regressions of shocks on FOMC day dummy				
	ω^g	ω^m	ω^{p+}	ω^{p-}
FOMC day dummy	0.097	-0.19	-0.12	-0.15*
	(0.99)	(-1.53)	(-1.53)	(-1.74)
Constant	-0.014	0.012	0.011	0.015
	(-0.80)	(0.68)	(0.68)	(0.98)
N (days)	3784	3784	3784	3784

Table VI. FOMC dummy regressions. The table reports regressions of model-based shocks on the FOMC announcement day dummy for scheduled FOMC announcements. Panel A presents results using absolute values of shocks, and panel B—using signed shocks. Shocks are expressed in units of standard deviations. Regressions are estimated over the 1994–2008 sample, covering 120 scheduled FOMC meetings. t-statistics robust to heteroskedasticity are reported in parentheses.

We are interested in establishing how innovations to these proxies comove with shocks from our identification. To construct innovations, we regress each proxy on its own lags, with the number of lags selected using the Bayesian information criterion (BIC). The results are not materially different if we use changes in each variable. Innovations between the measures of bond and equity premiums are essentially uncorrelated.[29] This fact demonstrates the challenge of jointly explaining the variation in risk premiums on stocks and bonds. CP and $\widehat{cf}$ are highly positively correlated at 0.69. Among measures of the equity premium, innovations in KP and CAY have a correlation of 0.14, while the highest correlation of KP (CAY) and the forward equity premiums equals 0.18 (0.53). Appendix Table IA-4 tabulates correlations across all variable pairs.

Our identification assumes that positive ω^{p-} shocks increase risk premiums on stocks and bonds, whereas positive ω^{p+} shocks increase risk premiums on stocks but decrease risk premiums on bonds. Therefore, we test whether innovations to measures of bond and equity premium load on ω_t shocks with the expected signs. Importantly, the risk premium proxies

[29]The exception is the correlation between $\widehat{cf}$ and forward equity premium from Martin (2017) which reaches negative -25% estimated over the 1996–2012 sample.

listed above do not imply (nor are constructed under the assumption) that shocks to risk premiums are uncorrelated with fundamentals. Indeed, one would expect that equity risk premiums vary over the business cycle in a countercyclical fashion (Lustig and Verdelhan, 2012); evidence for bond risk premiums is more mixed. Since we aim to decompose shocks to asset prices into four orthogonal components, it is of interest to study how much of variation in risk premium measures is explained by ω^{p+} and ω^{p-} alone.[30]

Table VII reports results for the bond risk premium. The ω^{p+} and ω^{p-} shocks alone explain 81% of monthly innovations in $\widehat{cf}$, while all four shocks explain 92%. The corresponding numbers for the CP factor are 49% and 51%. Excluding ω^{g} and ω^{m} does not materially change the regression loadings, with ω^{p-} being the most significant in economic terms. The loadings have the expected signs moving bond risk premiums in opposite directions: A one-standard-deviation positive ω^{p-} shock is associated with a 0.75 (0.55) standard deviations increase in $\widehat{cf}$ (CP) factor, while a one standard deviation ω^{p+} shock is associated with a -0.47 (-0.40) standard deviation decline of $\widehat{cf}$ (CP) factor.

Table VIII presents similar analysis for the equity risk premium. In panel A, we use data from Martin (2017), available daily for the 1996–2012 sample, to calculate forward equity premiums for months 0 to 1, 1 to 2, 2 to 3, as well as 4 to 6, 7 to 12, and 0 to 12. The explanatory power of the model-based shocks for innovations in the forward premiums declines with the maturity. All four shocks span 58% of daily changes in the 0 to 1 month premium, and 13% of variation in the 2 to 3 month premium. The loadings on ω^{p+} and ω^{p-} have both the expected (positive) sign, implying that positive shocks are associated with an increase in the equity risk premium. In terms of economic significance, the coefficients on ω^{p+} are about 50% larger than those on ω^{p-}. Turning to the KP and CAY variables in Panel B, we also find the coefficients on ω^{p-} and ω^{p+} are positive and statistically significant. Model-based shocks explain 8.1% of monthly innovations in KP and 21% of quarterly innovations in CAY, with two shocks ω^{p+} and ω^{p-} capturing 3.5% of variation in KP and 5.1% in CAY. The model-based growth (monetary) shocks have a negative (positive) impact on innovation in the equity premium across all alternative measures. These signs are consistent with the view

[30]Our identification imposes that shocks are orthogonal at the daily frequency over the 1983–2017 sample. When converting shocks to monthly or quarterly frequency, we sum shocks within the particular period. There is no guarantee that sums of shocks remain exactly orthogonal in subsamples or once converted to lower frequencies. However, we find that their correlations are generally low (see Appendix Table IA-5). To assess whether the correlation between shocks at lower frequencies distorts regression coefficients, in Tables VII and VIII, we report coefficients for four- and two-shock versions of the regressions, and find that the coefficients on the risk-premium shocks are very similar across the two versions.

that the risk premium in the equity market is countercyclical, i.e., positive growth news lowers the equity premium, as well as that the monetary tightening increases the equity premium (Bekaert et al., 2013). However, the results also suggest that a non-negligible fraction of variation in the risk premium on stocks, albeit a smaller one than for bonds, stems from pure risk-premium shocks.

	$\widehat{cf}$ innovations		CP innovations	
	(1)	(2)	(3)	(4)
ω^{p-}	0.753***	0.735***	0.551***	0.547***
	(42.06)	(19.43)	(10.69)	(11.52)
ω^{p+}	-0.467***	-0.476***	-0.404***	-0.402***
	(-30.57)	(-17.59)	(-12.22)	(-11.21)
ω^{g}	0.302***		0.125**	
	(16.75)		(2.23)	
ω^{m}	0.104***		0.001	
	(5.82)		(0.03)	
R^2	0.92	0.81	0.51	0.49
N (mth)	419	419	419	419

Table VII. Innovations to bond risk premium. The table reports regressions of innovations in bond risk premium on model-based shocks. As bond risk premium proxies, we construct estimates following Cieslak and Povala (2015) (columns (1) and (2)) and Cochrane and Piazzesi (2005) (columns (4) and (5)). Innovations to the bond risk premium proxies are computed as residuals from an AR(1) process, where the number of lags is selected using the BIC. (The results are very similar if we use simple changes instead of AR(1) residuals.) Monthly model-based shocks are obtained by summing up daily shocks within each month. This is consistent with the construction of bond risk premium proxies, which uses end of month data. Regression coefficients are standardized. Regressions are estimated at the monthly frequency over the 1983–2017 sample. t-statistics robust to heteroskedasticity are reported in parentheses.

VII. Conclusions

How important are monetary policy shocks in driving asset prices? How important are those shocks vis-a-vis shocks to investors' expectations about economic activity and pure risk-premium shocks that are unrelated to the fundamentals? There are several challenges in answering those questions. For one, shocks to investor macroeconomic and policy expectations are not directly observable. Even if one can "observe" shocks through the timing of announcement events, news does not come out only at the time of announcements, and the news content of announcements themselves is multidimensional. Fluctuations in the risk premium additionally compound these identification challenges.

We propose a new approach to analyzing the sources of variation in asset prices, focusing on the Treasury yields and the stock market. We exploit the fact that mainstream asset pricing

A. Daily changes in forward equity risk premium						
	(1) $0 \to 1m$	(2) $1 \to 2m$	(3) $2 \to 3m$	(4) $4 \to 6m$	(5) $7 \to 12m$	(6) $0 \to 12m$
ω^{p-}	0.289***	0.243***	0.095***	0.185***	0.096***	0.248***
	(11.15)	(12.88)	(6.75)	(11.05)	(4.01)	(14.54)
ω^{p+}	0.426***	0.388***	0.219***	0.301***	0.194***	0.419***
	(17.53)	(18.33)	(12.09)	(16.81)	(10.96)	(23.34)
ω^{g}	-0.344***	-0.298***	-0.165***	-0.238***	-0.193***	-0.350***
	(-17.06)	(-15.75)	(-9.84)	(-12.84)	(-8.74)	(-19.97)
ω^{m}	0.261***	0.244***	0.133***	0.191***	0.154***	0.276***
	(11.50)	(13.50)	(8.06)	(11.87)	(8.63)	(17.70)
R^2	0.58	0.46	0.13	0.28	0.14	0.56
$R^2(\omega^{p-}, \omega^{p+})$	0.41	0.32	0.090	0.20	0.082	0.38
N (days)	4054	4054	4054	4054	4054	4054

B. Alternative measures of equity risk premium

	KP innovations (mth)		CAY innovations (qtr)	
	(1)	(2)	(3)	(4)
ω^{p-}	0.153**	0.162**	0.186**	0.155*
	(2.55)	(2.57)	(2.51)	(1.86)
ω^{p+}	0.232***	0.183**	0.136	0.174*
	(3.09)	(2.56)	(1.44)	(1.89)
ω^{g}	-0.203***		-0.370***	
	(-2.64)		(-3.84)	
ω^{m}	0.300***		0.280***	
	(2.99)		(3.51)	
R^2	0.081	0.035	0.21	0.051
N	336	336	138	138

Table VIII. Innovations to equity risk premium. The table presents regressions of innovations in measures of the equity risk premium on model-based shocks. In panel A, the dependent variables are daily changes in the forward equity risk premium at different maturities. The forward equity premium data is from Martin (2017). The explanatory variables are daily model-based shocks. For comparison with the four-shock regressions, row labelled "$R^2(\omega^{p-}, \omega^{p+})$" reports the R^2 from regressions using only two shocks, ω^{p-}, ω^{p+}. Detailed regression results for the two-shock specification are reported in Appendix Table IA-6. Panel B contains results based on alternative risk premium proxies: the factor from Kelly and Pruitt (2013, KP) in column (1) and (2) and the CAY variable from Lettau and Ludvigson (2001). KP's measure is available monthly, and CAY is available quarterly, both obtained from respective authors' websites. The innovations to KP and CAY are residuals of an AR process with lag numbers selected using the BIC, resulting in 3 monthly lags for KP and 2 quarterly lags for CAY. Monthly (quarterly) model-based shocks are generated by summing up daily shocks within calendar month (quarter). Depending on the data availability, the estimates cover different samples. Martin's forward equity premium in panel A is available for Jan 5, 1996–Jan 31, 2012. The KP data ends in Dec 2010, and CAY data ends in the 3rd quarter of 2017; in panel B, the sample starts in 1983. Robust t-statistics are reported in parentheses.

models have a structural VAR representation. Economically interesting shocks can thus be uncovered from reduced-form VAR dynamics of asset prices combined with restrictions of how economic shocks affect those prices. Using motivation from theoretical models, we impose restrictions on how different shocks affect the joint dynamics of the stock market and the Treasury yield curve across maturities. With this approach, we identify the properties of shocks to investors' expectations about monetary policy, shocks to growth expectations and pure risk-premium shocks. We trace out the effects of those shocks on any day (as opposed to an event-study approach), over a long-sample period, and for both equities and bonds. We use our identification to study the drivers of stock and bonds returns over the FOMC cycle, and quantify the importance of different shocks for asset prices since the early 1980s.

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Internet Appendix for:

Common shocks in stocks and bonds

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A. Model illustration

In Section II.B, we consider an asset pricing model with factors including expected inflation, expected consumption growth, monetary policy and two market prices of risk following VAR(1):

$$F_{t+1} = \mu_F + \Phi_F F_t + \Sigma_F \omega_{t+1}, \tag{IA.22}$$

where $F_t = (\tau_t, g_t, m_t, x_t^+, x_t^-)'$, $\omega_{t+1} = (\omega_{t+1}^\tau, \omega_{t+1}^g, \omega_{t+1}^m, \omega_{t+1}^{x+}, \omega_{t+1}^{x-})'$. The nominal one-period interest rate is

$$i_t = \delta_0 + \delta_\tau \tau_t + \delta_g g_t + m_t = \delta_0 + \delta_1' F_t, \tag{IA.23}$$

where $\delta_1 = (\delta_\tau, \delta_g, 1, 0, 0)'$. The nominal log stochastic discount factor (SDF) has the form

$$\xi_{t+1} = \ln M_{t+1} = -i_t - \frac{1}{2}\Lambda_t'\Lambda_t - \Lambda_t'\omega_{t+1}, \tag{IA.24}$$

where $\Lambda_t = \Sigma_F^{-1}(\lambda_0 + \Lambda_1 F_t)$, and the real log SDF is $\xi_{t+1}^r = \xi_{t+1} + \pi_{t+1}$. We assume that matrix Λ_1 has all elements equal to zero but for $\Lambda_{1(2,4)} = \lambda_{gx^+}$ and $\Lambda_{1(3,5)} = \lambda_{mx^-}$. Letting $p_t^{(n)}$ denote the log bond price, and given yields $y_t^{(n)} = \frac{1}{n}p_t^{(n)}$, we conjecture that yields are affine in the state variables:

$$\begin{aligned} y_t^{(n)} &= b_n + B_n' F_t \\ p_t^{(n)} &= -n y_t^{(n)} = -n b_n - n B_n' F_t. \end{aligned} \tag{IA.25}$$

Given that equilibrium bond prices satisfy

$$\exp(p_t^{(n)}) = E_t[\exp(\xi_{t+1} + p_{t+1}^{(n-1)})], \tag{IA.26}$$

solving by iteration and using the property of log-normal distribution, the yield loadings on the state are

$$B_n = \frac{n-1}{n}(\Phi - \Lambda_1)' B_{n-1} + \frac{1}{n}\delta_1. \tag{IA.27}$$

The one-period expected log excess bond returns are:

$$E_t(rx_{t+1}^{(n)}) + \frac{1}{2}Var_t(rx_{t+1}^{(n)}) = -Cov_t(\xi_{t+1}, \frac{p_{t+1}^{(n-1)}}{p_t^{(n)}}). \tag{IA.28}$$

The solution for stock return relies on the standard Campbell-Shiller log-linearization:

$$r_{t+1}^s = \kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t. \tag{IA.29}$$

Then, in equilibrium the log pd ratio is also affine in the state:

$$pd_t = b_s + B_s' F_t. \tag{IA.30}$$

Using the fact that stock returns satisfy

$$\ln E_t[\exp(\xi_{t+1}^r + r_{s,t+1})] = 0, \tag{IA.31}$$

we solve for the loadings for the pd ratio in the state:

$$B_s' = (\delta_1' - \theta')[\kappa_1(\Phi_F - \Lambda_1) - I]^{-1}, \tag{IA.32}$$

where $\theta = (1, 1, 0, 0, 0)'$, and I is a 5×5 identity matrix. Finally, one-period expected log excess stock return is

$$E_t(rx^s_{t+1}) + \frac{1}{2}Var_t(rx^s_{t+1}) = -Cov_t(\xi^r_{t+1}, r^s_{t+1}). \tag{IA.33}$$

The table below summarizes the assumptions and the model solutions:

Model specification	$\Phi_F = \text{diag}(\phi_\tau,\phi_g,\phi_m,\phi_{x^+},\phi_{x^-})$ $\Lambda_{1(2,4)} = \lambda_{gx^+} > 0$, $\Lambda_{1(3,5)} = \lambda_{mx^-} < 0$ $0 < \delta_g < 1$ and $\delta_\tau > 1$
Yields loadings	$B^i_n = \frac{\delta_i}{n}\frac{1-\phi_i^n}{1-\phi_i} > 0$, $i = \{\tau, g, m\}$ $B^{x^+}_n = \frac{n-1}{n}\phi_{x^+}B^{x^+}_{n-1} - \frac{n-1}{n}B^g_{n-1}\lambda_{gx^+} < 0$ $B^{x^-}_n = \frac{n-1}{n}\phi_{x^-}B^{x^-}_{n-1} - \frac{n-1}{n}B^m_{n-1}\lambda_{mx^-} > 0$
pd ratio loadings	$B^g_s = \frac{1-\delta_g}{1-\kappa_1\phi_g} > 0$ $B^\tau_s = \frac{1-\delta_\tau}{1-\kappa_1\phi_\tau} < 0$ $B^m_s = -\frac{1}{1-\kappa_1\phi_m} < 0$ $B^{x^+}_s = \frac{-\kappa_1\lambda_{gx^+}B^g_s}{1-\kappa_1\phi_{x^+}} < 0$ $B^{x^-}_s = \frac{-\kappa_1\lambda_{fx^-}B^m_s}{1-\kappa_1\phi_{x^-}} < 0$
Bond expected excess returns	$\text{const.}\underbrace{-(n-1)B^g_{n-1}}_{(-)}\lambda_{gx^+}x^+_t \underbrace{-(n-1)B^m_{n-1}}_{(-)}\lambda_{mx^-}x^-_t$
Stock expected excess returns	$\text{const.}+\kappa_1(\underbrace{B^g_s}_{(+)}\lambda_{gx^+}x^+_t + \underbrace{B^m_s}_{(-)}\lambda_{mx^-}x^-_t)$

Allowing for feedbacks between factors (i.e., non-diagonal Φ_F), makes the coefficients more complex. However, under empirically realistic assumptions, the intuition obtained from the diagonal case still holds. When $\Phi_{F(2,1)} = \phi_{g\tau} < 0$, expected inflation shocks negatively affect future expected growth and $B^\tau_n = \frac{n-1}{n}\phi_\tau B^\tau_{n-1} + \frac{n-1}{n}\phi_{g\tau}B^g_{n-1} + \frac{\delta_\tau}{n}$ and $B^\tau_s = \frac{1+\kappa_1\phi_{g\tau}B^g_s-\delta_\tau}{1-\kappa_1\phi_\tau}$ with expressions for other loadings unchanged. Thus, the negative feedback $\phi_{g\tau}$ strengthens the negative effect of τ_t on stocks. However, estimating a VAR(1) model with survey expectations of real GDP growth and inflation, we find that such a feedback effect is not statistically significantly different from zero in the post-1983 sample (see footnote 15 in the paper). When $\Phi_{F(2,3)} = \phi_{gm} < 0$, expected monetary policy negatively affect expected growth. Then, $B^m_n = \frac{n-1}{n}\phi_m B^m_{n-1} + \frac{n-1}{n}\phi_{gm}B^g_{n-1} + \frac{1}{n}$ and $B^m_s = \frac{\kappa_1\phi_{gm}B^g_s-1}{1-\kappa_1\phi_m} < 0$ with expressions for other loadings unchanged. When the negative feedback of monetary policy on expected growth is not too strong, we have $B^m_n > 0$ across maturities (in line with the empirical literature) and thus, the sign of the loadings remain as in the diagonal Φ_F case.

B. Loadings on long-term yields under the expectations hypothesis

Consider a pure expectations hypothesis (EH) case. Under the EH, the long term yield is the average of expected future short rates:

$$y^{(n)}_t = \frac{1}{n}E_t\left(\sum_{i=0}^{n-1} y^{(1)}_{t+i}\right). \tag{IA.34}$$

In the affine dynamic term structure models the short rate is: $y_t^{(1)} = \gamma_0 + \gamma' X_t$, where X_t are the state variables. It is common to specify X_t as a VAR(1) process with a mean reversion matrix Φ (omitting constants for simplicity):

$$X_t = \Phi X_{t-1} + \epsilon_t. \tag{IA.35}$$

Then, under the EH, the long-term yield is

$$y_t^{(n),EH} = \text{const.} + \frac{1}{n}\gamma'(I-\Phi)^{-1}(I-\Phi^n)X_t. \tag{IA.36}$$

Suppose all eigenvalues of Φ are real and distinct, then $\Phi = C\Lambda C^{-1}$, Λ is the diagonal matrix of eigenvalues with elements λ_i, $\lambda_j \neq \lambda_i$, C is the matrix of associated eigenvectors. Let $Z_t = C^{-1}X_t$, then

$$Z_t = \Lambda Z_{t-1} + C^{-1}\epsilon_t. \tag{IA.37}$$

The short rate is $y_t^{(1)} = \gamma' X_t = \gamma' C Z_t$, and the long-term rate is

$$y_t^{(n)} - \text{const.} = \gamma'(\frac{1}{n}(I-\Phi)^{-1}(I-\Phi^n))X_t = \gamma'(\frac{1}{n}\sum_i^{n-1}\Phi^i)X_t = \tag{IA.38}$$

$$\gamma'(\frac{1}{n}\sum_i^{n-1}C\Lambda^i C^{-1})CZ_t = \gamma' C(\frac{1}{n}\sum_i^{n-1}\Lambda^i)Z_t = \gamma' C\tilde{\Lambda}Z_t \tag{IA.39}$$

where $\tilde{\Lambda}$ is diagonal with element i given by $\tilde{\lambda}_i = \frac{1}{n}\frac{1-\lambda_i^n}{1-\lambda_i}$, $\tilde{\lambda}_i < 1$ if $\lambda_i < 1$. So as n increases the impact of the short rate shocks will be dampened as long as elements of $\tilde{\Lambda}$ are less then unity, $|\lambda_i| < 1$, analogous to the univariate AR(1) case.

C. Additional tables and figures

Study	Effect on stocks	Effect on yields	Main sample period
Monetary shocks (tightening news)			
Poole et al. (2002)		+, ↘	pre-1994, 1994-2002
Rigobon and Sack (2004)	−	+, ↘	1994:1-2001:11
Gürkaynak et al. (2005b)		+, ↘	1990:1-2002:12
Bernanke and Kuttner (2005)	−	+, ↘	1989:6-2002:12
Gürkaynak et al. (2005a)	−	+, ↘	1990:1-2004:12
Campbell et al. (2012)		+, ↘	1990:2-2007:6, 2007:8-2011:12
Hanson and Stein (2015)		+, ↘	1999:1-2012:2
Nakamura and Steinsson (2018)	−	+, ↘	1995-2014

Table IA-1. Literature on identification of monetary shocks and their effect of stocks and the yield curve. The table summarizes the evidence on the effect of monetary policy shocks on stocks and yields. + (−) describes the direction of the effect, ↘ indicates that the effect declines across the term structure.

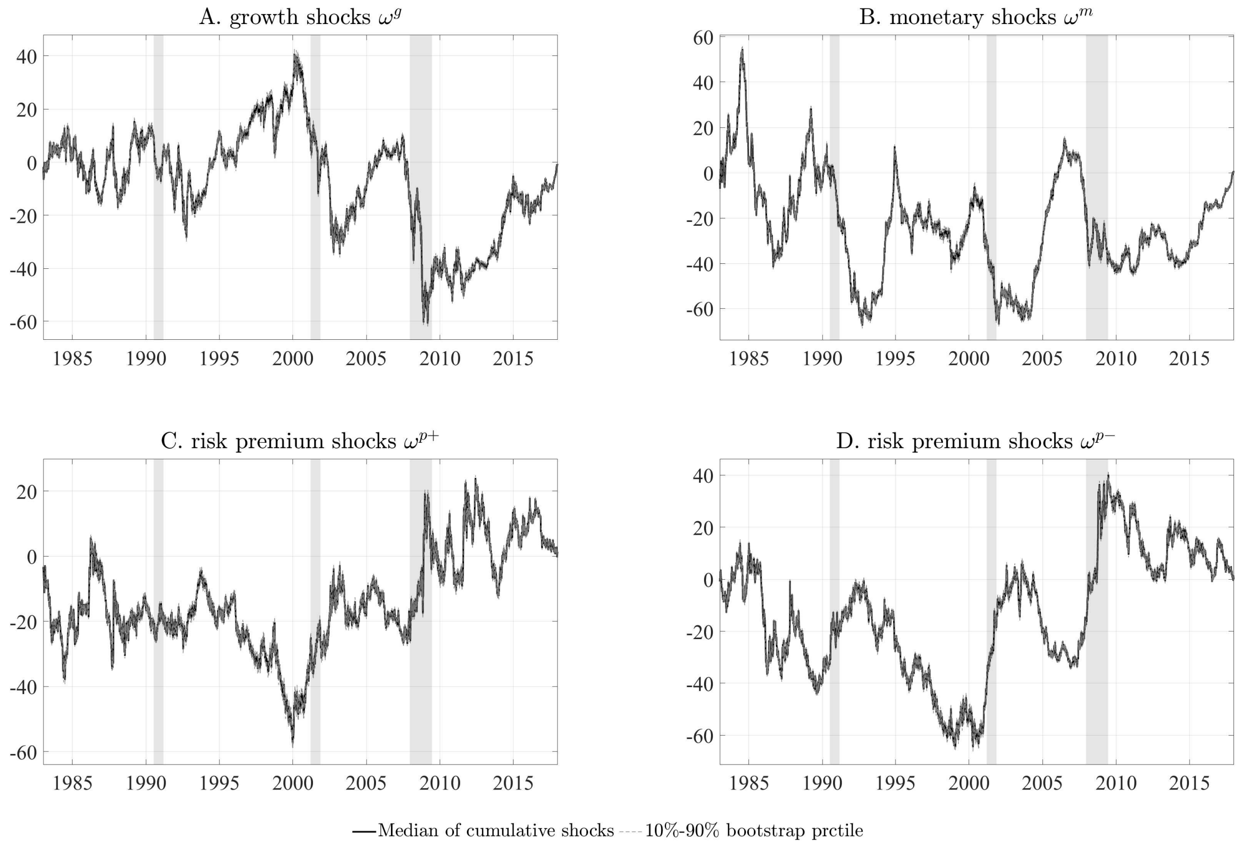

Figure IA-1. Estimation uncertainty. The figure presents 10-90% bootstrap confidence interval around the median of cumulative shocks.

	A. Sample 1998–2017				B. Sample 1983–2007				
	ω^g	ω^m	ω^{p+}	ω^{p-}		ω^g	ω^m	ω^{p+}	ω^{p-}
ω^g	0.98***				ω^g	1.01***			
	(217.27)					(517.62)			
ω^m		1.04***			ω^m		0.93***		
		(151.73)					(297.86)		
ω^{p+}			0.93***		ω^{p+}			1.08***	
			(329.17)					(246.88)	
ω^{p-}				1.07***	ω^{p-}				0.99***
				(203.20)					(437.34)
Const.	0.0039	-0.0058	-0.0068***	-0.013***	Const.	0.0024**	0.0024	0.0049***	0.0031***
	(1.28)	(-1.45)	(-3.59)	(-4.52)		(2.23)	(1.10)	(2.66)	(3.18)
R^2	0.953	0.919	0.982	0.958	R^2	0.993	0.970	0.979	0.994
N	5039	5039	5039	5039	N	6310	6310	6310	6310

Table IA-2. Subsample estimates. The table reports regressions of shocks estimated over subsamples (1998–2017 in panel A and 1983–2007 in panel B) on shocks estimated over the full sample (1983–2017). All shocks are observed at the daily frequency and are expressed in units of standard deviations. Robust t-statistics are in parentheses.

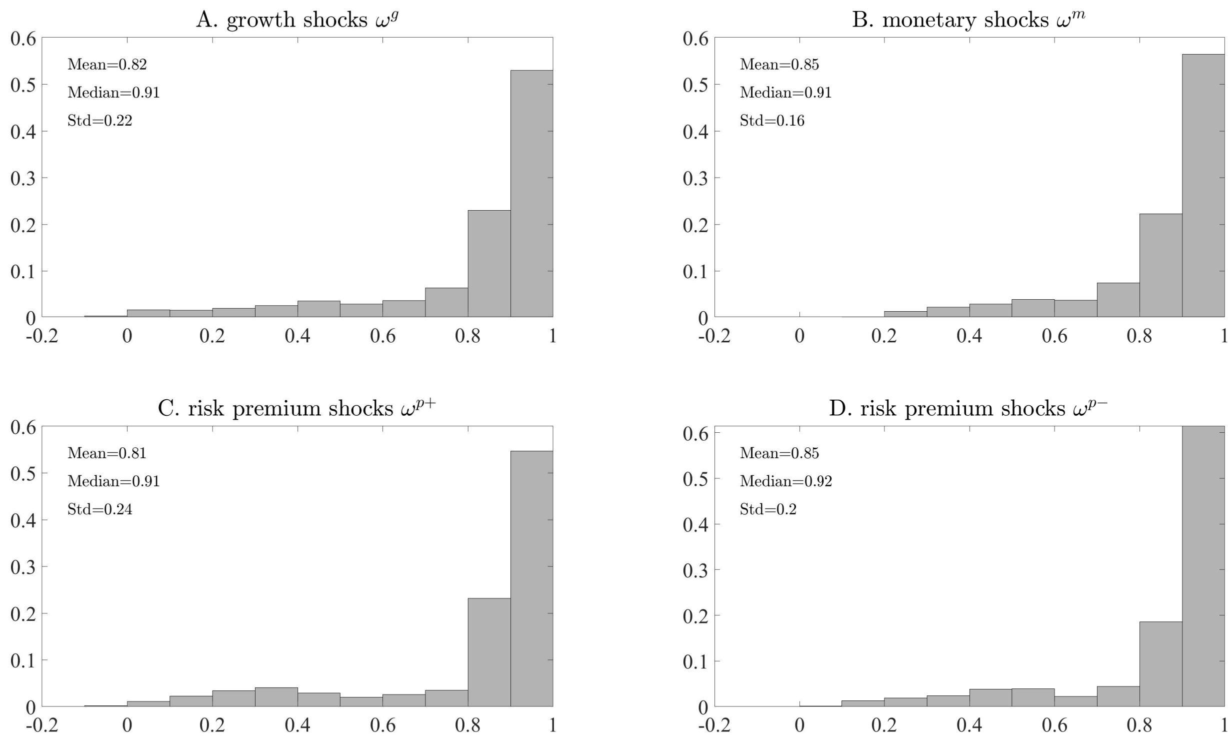

Figure IA-2. Correlation of shocks from different models. The figure presents the distribution of correlation coefficients across all retained solutions. For each structural shock j associated with solution i we calculate its correlation with shock j associated with the MT solution, and plot the histogram of the correlation coefficients across all retained solutions.

	(1) $h=0$	(2) $h=1$	(3) $h=2$	(4) $h=3$	(5) PCA
$\text{Updt}^{BC}(g_h)$	0.533***	0.536***	0.394***	0.240**	
	(8.18)	(10.06)	(5.06)	(2.15)	
PC1					0.511***
					(9.95)
PC2					0.250***
					(4.62)
PC3					0.035
					(0.45)
PC4					-0.022
					(-0.34)
R^2	0.28	0.29	0.16	0.058	0.33
N	417	417	417	417	417

Table IA-3. Growth shocks (3-month cumulative). The table reports regressions of growth shocks obtained with our identification scheme on contemporaneous real GDP growth expectations updates from the BCEI survey. Model shocks and survey updates are cumulated over the past $k=3$ months and are sampled monthly. The regressions are estimated at the monthly frequency over the sample period 1983–2017. Slope coefficients are standardized with left- and right-hand side variables measured in z-scores. T-statistics in parentheses are Newey-West adjusted with 7 lags to account for overlapping data.

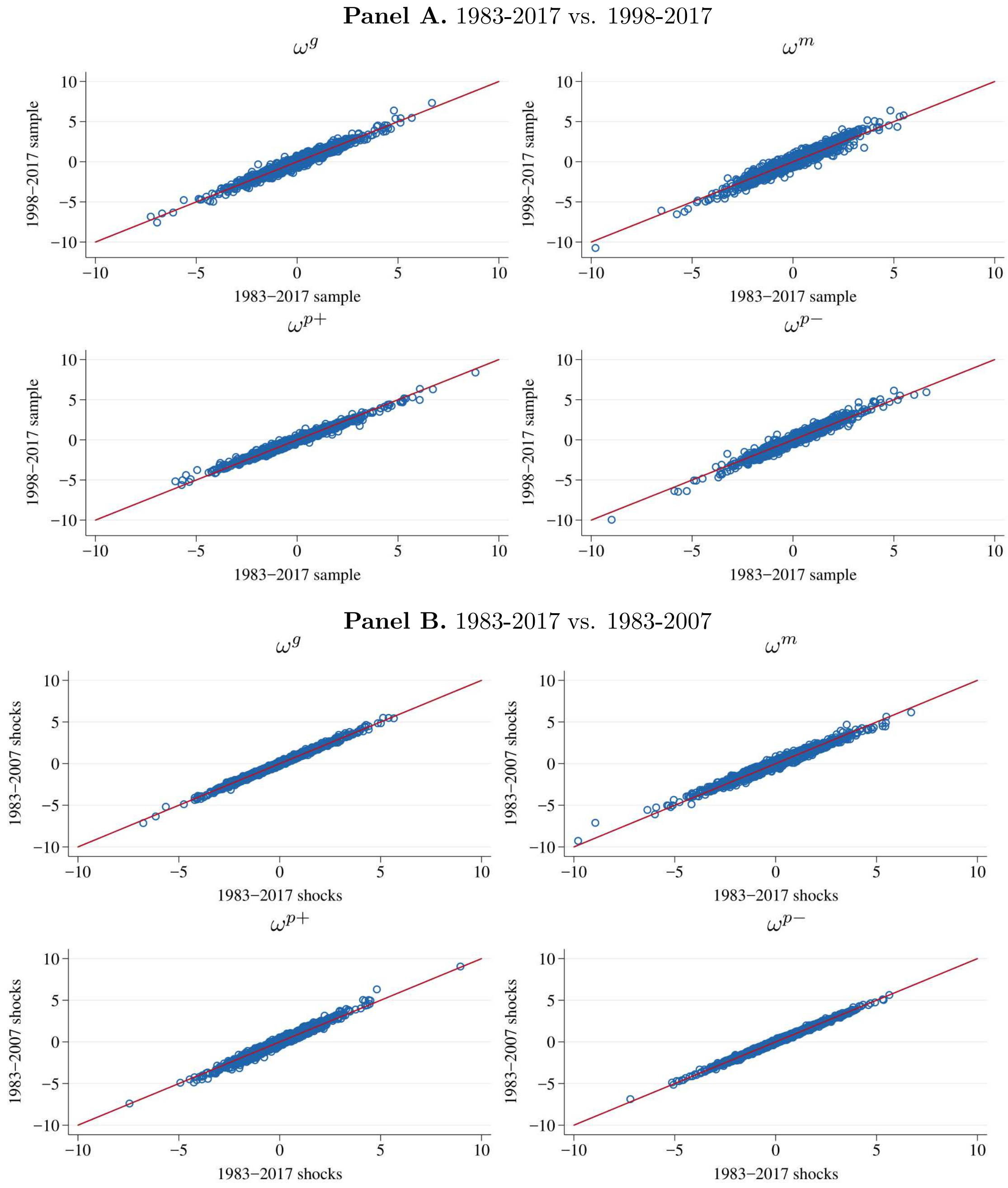

Figure IA-3. Shocks estimated over subsamples. The figure presents scatter plots of shocks estimated over different samples. We compare shocks estimated over the 1983–2017 sample with those estimated over the 1998–2017 subsample (Panel A) and 1983–2007 subsample (panel B). Each plot contains a 45-degree line.

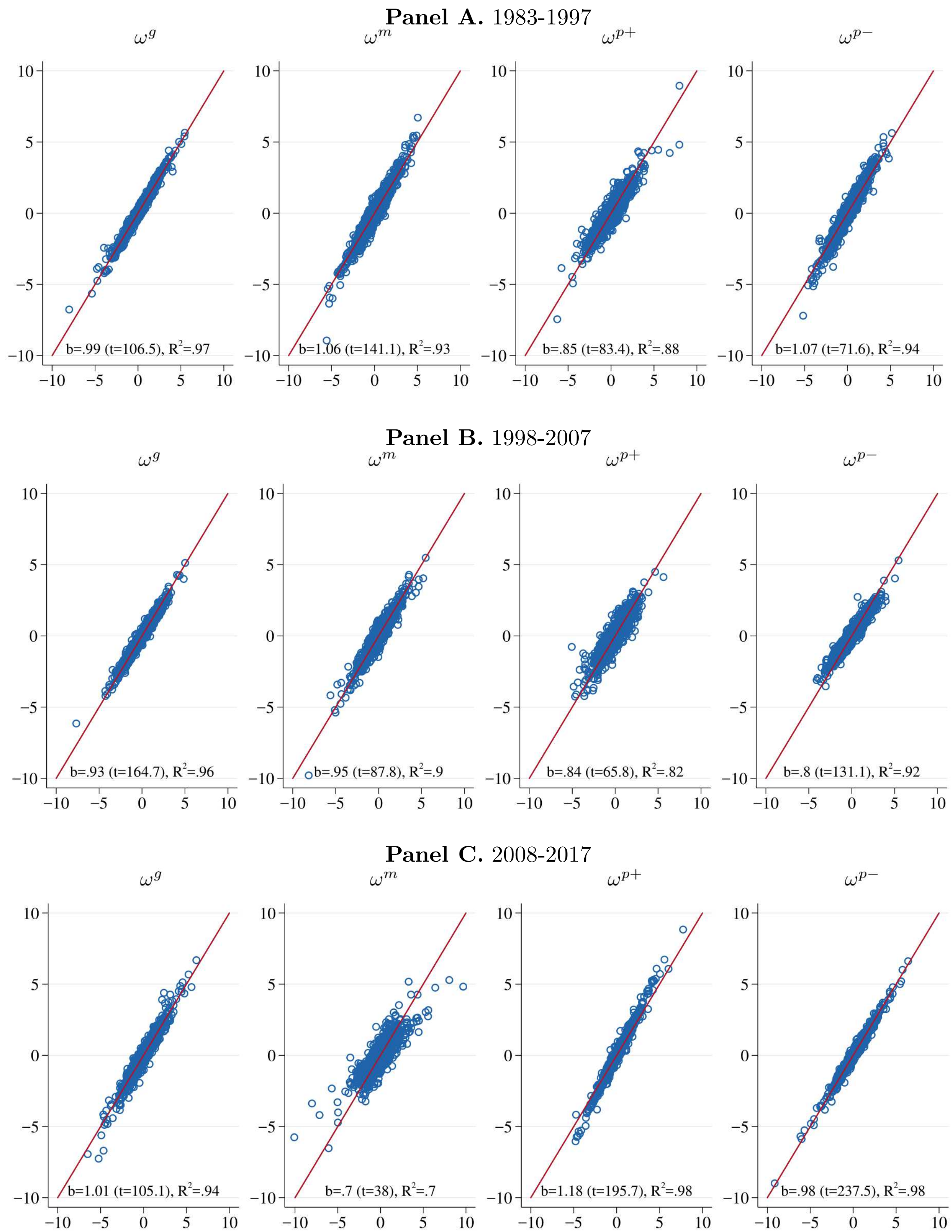

Figure IA-4. Shocks estimated over subsamples. The figure presents scatter plots of shocks estimated over the full sample, 1983–2017 (on the y-axis) against shocks estimated over subsamples (on the x-axis). Each plot contains a 45-degree line,and reports the slope coefficient, robust t-statistic and R^2 from a regression of full-sample shocks on the subsample shocks. The subsample shocks are guaranteed to have a unit standard deviation, thus the coefficients less than one means that full-sample shocks are less volatile than subsample shocks in a given period.

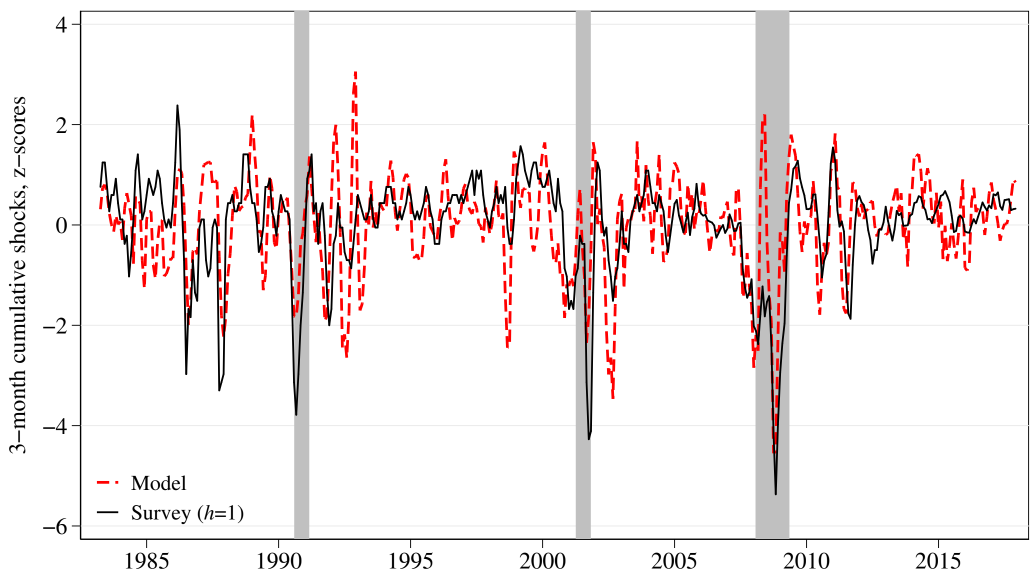

Figure IA-5. Comparison of model-based shocks with survey forecast updates for real GDP growth (3-month cumulative). The figure superimposes growth shocks from the model with the forecast updates of real GDP growth expectations from the BCEI survey. The shocks and survey updates are cumulative over a 3-month period. Survey updates are for one quarter ahead ($h = 1$). Both variables are standardized to have a zero mean and unit standard deviation.

A. Monthly frequency

Variables	$\widehat{cf}$	CP	KP	EP 0-1m	EP 1-2m	EP 2-3m	EP 4-6m	EP 7-12m
$\widehat{cf}$	1.00							
CP	0.69	1.00						
	(0.00)							
	419							
KP	0.02	-0.05	1.00					
	(0.76)	(0.41)						
	335	335						
EP 0-1m	-0.12	0.05	0.17	1.00				
	(0.10)	(0.53)	(0.02)					
	190	190	177					
EP 1-2m	-0.18	-0.00	0.18	0.91	1.00			
	(0.01)	(0.95)	(0.02)	(0.00)				
	190	190	177	190				
EP 2-3m	-0.25	-0.07	0.11	0.56	0.78	1.00		
	(0.00)	(0.33)	(0.16)	(0.00)	(0.00)			
	192	192	179	190	190			
EP 4-6m	-0.20	-0.03	0.11	0.75	0.84	0.79	1.00	
	(0.01)	(0.64)	(0.14)	(0.00)	(0.00)	(0.00)		
	192	192	179	190	190	192		
EP 7-12m	-0.09	0.05	0.08	0.57	0.62	0.50	0.59	1.00
	(0.23)	(0.48)	(0.27)	(0.00)	(0.00)	(0.00)	(0.00)	
	192	192	179	190	190	192	192	

B. Quarterly frequency

Variables	$\widehat{cf}$	CP	KP	EP 0-1m	EP 1-2m	EP 2-3m	EP 4-6m	EP 7-12m	CAY
CAY	-0.01	-0.07	0.14	0.53	0.51	0.48	0.47	0.38	1.00
	(0.89)	(0.43)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
	138	138	112	63	63	63	63	63	

Table IA-4. Correlations of innovations to measures of bond and equity risk premium. The table presents correlations of innovations to alternative measures of bond and equity risk premium from Cieslak and Povala (2015, $(\widehat{cf})$) , Cochrane and Piazzesi (2005, CP), Kelly and Pruitt (2013, KP), Martin (2017, EP), and Lettau and Ludvigson (2001, CAY). The innovations are obtained as residuals from an AR(p) process, with the number of lags selected using BIC. The p-values are included in parentheses. For each pair of variables, we also report the number of observations involved in the calculation. Since CAY is available at the quarterly frequency, its correlations with all other variables are reported separately in Panel B. Expect for forward equity premia (EP), the sample starts in 1983. The end of the sample depends on the data availability as reported in Tables VII and VIII.

A. Monthly frequency				
Variables	ω^g	ω^m	ω^{p+}	ω^{p-}
ω^g	1.00			
ω^m	0.13	1.00		
	(0.01)			
	420			
ω^{p+}	0.03	-0.14	1.00	
	(0.57)	(0.00)		
	420	420		
ω^{p-}	-0.03	-0.07	-0.07	1.00
	(0.49)	(0.14)	(0.15)	
	420	420	420	

B. Quarterly frequency				
Variables	ω^g	ω^m	ω^{p+}	ω^{p-}
ω^g	1.00			
ω^m	0.25	1.00		
	(0.00)			
	139			
ω^{p+}	-0.23	-0.17	1.00	
	(0.01)	(0.05)		
	139	139		
ω^{p-}	-0.10	-0.24	-0.05	1.00
	(0.26)	(0.00)	(0.53)	
	139	139	139	

Table IA-5. Correlations of aggregated model-based shocks. The table displays correlations of monthly and quarterly sums of daily shocks from the model. The model is estimated at the daily frequency over the 1983–2017 sample. Daily shocks are uncorrelated by construction.

	(1)	(2)	(3)	(4)	(5)	(6)
	$0 \to 1m$	$1 \to 2m$	$2 \to 3m$	$4 \to 6m$	$7 \to 12m$	$0 \to 12m$
ω^{p-}	0.310***	0.261***	0.105***	0.199***	0.107***	0.269***
	(10.45)	(11.69)	(7.14)	(10.54)	(4.47)	(13.27)
ω^{p+}	0.539***	0.487***	0.274***	0.380***	0.259***	0.535***
	(16.46)	(17.67)	(13.90)	(18.73)	(12.59)	(21.54)
R^2	0.41	0.32	0.090	0.20	0.082	0.38
N (days)	4054	4054	4054	4054	4054	4054

Table IA-6. Innovations to forward equity risk premium. The table presents details of bi-variate regressions of innovations in forward equity premium on ω^{p+} and ω^{p-} shocks to accompany Table VIII Panel A in the paper.

A. 1983–2017 sample	$\Delta y^{(2)}$	$\Delta y^{(5)}$	$\Delta y^{(10)}$	Δs
ω^g	0.38	0.35	0.11	0.26
	0.32	0.28	0.11	0.29
	(0.19)	(0.18)	(0.11)	(0.24)
ω^m	0.43	0.16	0.09	0.17
	0.44	0.21	0.11	0.17
	(0.20)	(0.15)	(0.11)	(0.19)
ω^{p+}	0.12	0.15	0.35	0.32
	0.15	0.23	0.38	0.29
	(0.12)	(0.17)	(0.19)	(0.24)
ω^{p-}	0.08	0.34	0.46	0.24
	0.10	0.27	0.39	0.26
	(0.10)	(0.17)	(0.18)	(0.22)

B. 1983–1997 sample	$\Delta y^{(2)}$	$\Delta y^{(5)}$	$\Delta y^{(10)}$	Δs
ω^g	0.22	0.21	0.03	0.21
	0.26	0.27	0.08	0.14
	(0.17)	(0.16)	(0.09)	(0.15)
ω^m	0.54	0.25	0.16	0.21
	0.50	0.25	0.15	0.16
	(0.20)	(0.16)	(0.13)	(0.17)
ω^{p+}	0.15	0.21	0.43	0.08
	0.13	0.18	0.34	0.14
	(0.12)	(0.14)	(0.17)	(0.15)
ω^{p-}	0.08	0.33	0.39	0.51
	0.11	0.30	0.42	0.56
	(0.11)	(0.15)	(0.17)	(0.22)

C. 1998–2007 sample	$\Delta y^{(2)}$	$\Delta y^{(5)}$	$\Delta y^{(10)}$	Δs
ω^g	0.44	0.39	0.16	0.35
	0.36	0.32	0.16	0.33
	(0.19)	(0.18)	(0.12)	(0.24)
ω^m	0.42	0.21	0.19	0.07
	0.39	0.22	0.13	0.10
	(0.18)	(0.16)	(0.12)	(0.14)
ω^{p+}	0.09	0.20	0.42	0.29
	0.17	0.25	0.39	0.33
	(0.13)	(0.15)	(0.18)	(0.23)
ω^{p-}	0.05	0.20	0.24	0.29
	0.08	0.20	0.31	0.24
	(0.09)	(0.14)	(0.16)	(0.20)

D. 2008–2017 sample	$\Delta y^{(2)}$	$\Delta y^{(5)}$	$\Delta y^{(10)}$	Δs
ω^g	0.38	0.28	0.05	0.25
	0.40	0.29	0.10	0.32
	(0.20)	(0.17)	(0.10)	(0.24)
ω^m	0.40	0.12	0.04	0.05
	0.35	0.13	0.04	0.12
	(0.16)	(0.09)	(0.05)	(0.13)
ω^{p+}	0.16	0.28	0.51	0.58
	0.18	0.28	0.45	0.47
	(0.13)	(0.18)	(0.19)	(0.25)
ω^{p-}	0.07	0.33	0.40	0.11
	0.07	0.29	0.41	0.09
	(0.08)	(0.15)	(0.17)	(0.11)

Table IA-7. Variance decompositions. The table summarizes variance decompositions of daily yield changes and stock market returns into contributions of structural shocks across retained solutions. The top number in an asset-shock cell is the fraction of variance explained by shocks from the MT solution. The middle number in an asset-shock cell is the average fraction of variance explained, with average taken across retained solutions. In parentheses is the standard deviation of that fraction across retained solutions. Panel A uses full-sample estimates (1983–2017). Panels B through D are based on separate estimates over subsamples.

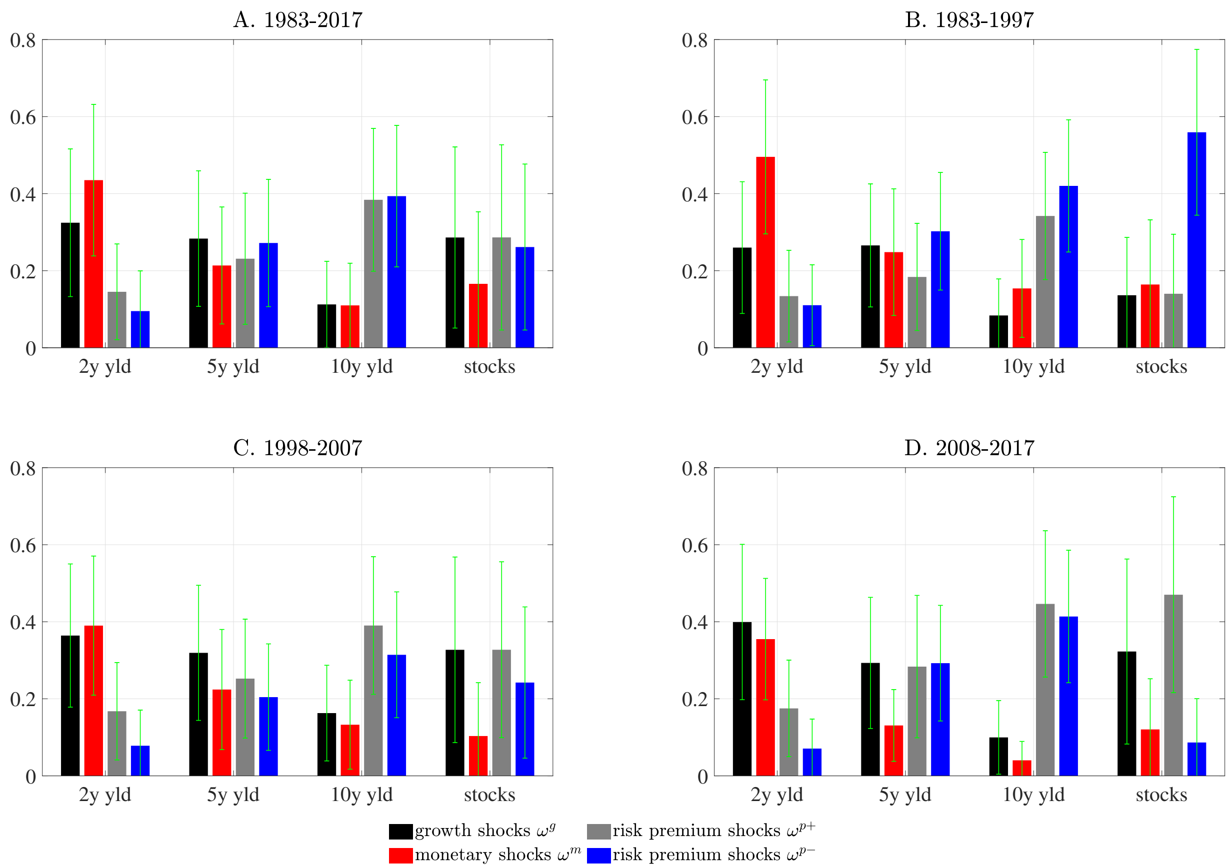

Figure IA-6. Variance decompositions. The figure presents variance decompositions of daily yield changes and stock market returns. The bars show the average fraction of variance explained by each shock, with average of that fraction taken across retained solutions. The error bars display one standard deviation of that fraction across retained solutions. Panel A reports full-sample estimates over the 1983–2017 period. Panels B through D are based on separate estimates for subsamples. These results accompany Figure 2, which presents variance decompositions for the MT solution.

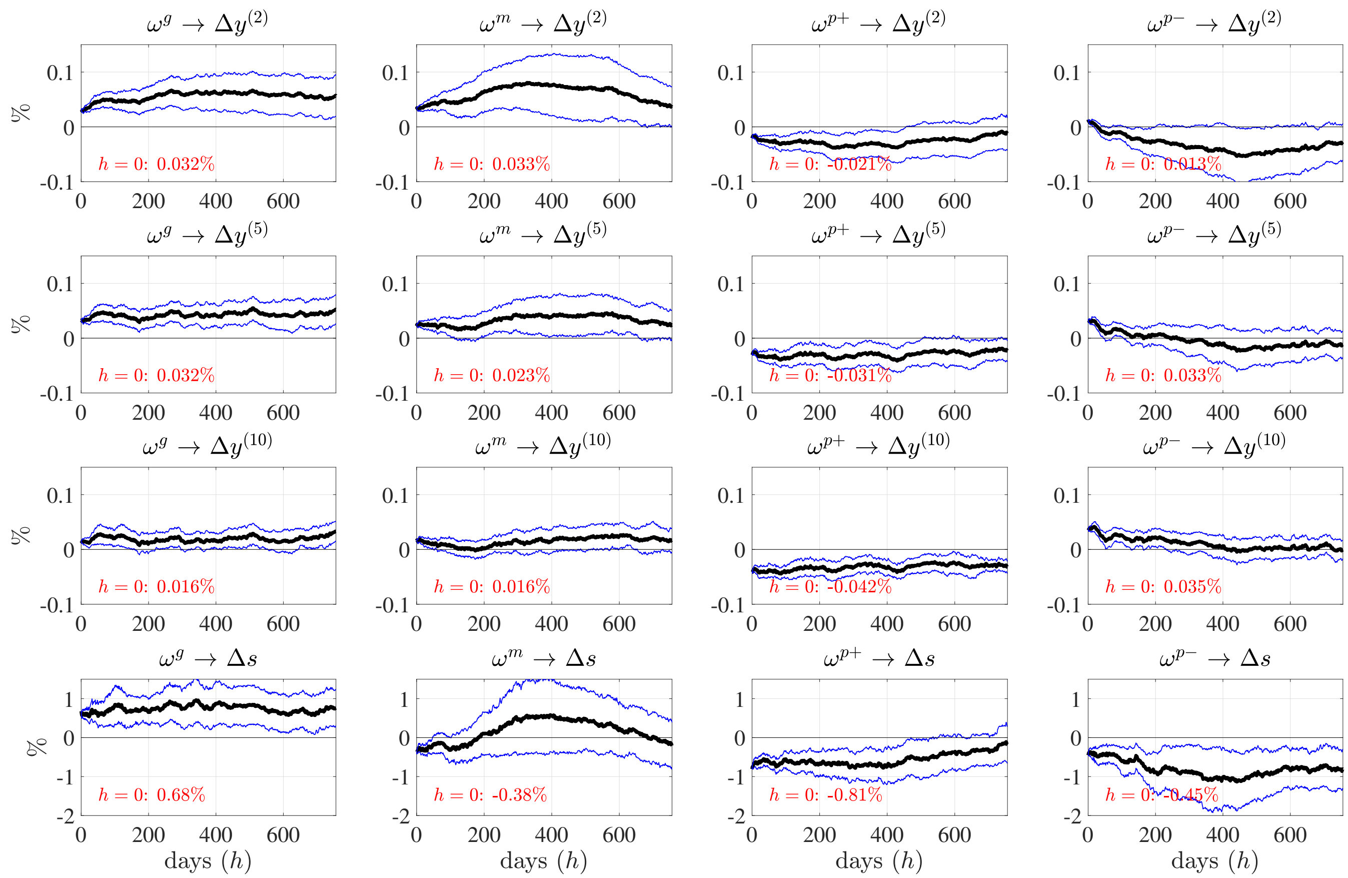

Figure IA-7. Impulse-response functions (1998–2017 sample). The figure presents impulse-response functions of yield changes and log stock returns to structural shocks. The shocks and the impulse responses are estimated on the 1998–2017 sample for comparison with Figure 3 in the paper, which is based on the 1983–2017 sample. Shocks are measured in units of standard deviation. Yield changes and stock returns are in percent. The solid thick line traces out the coefficients $\beta_h^{j,i}$ from regression (21). A coefficient of 0.1 (1) implies an asset response of 0.1% (1%) to a one standard deviation shock. The thin lines mark two-standard-error bands calculated with HAC adjustment using $h+1$ lags. In the bottom left corner of each graph, we display the coefficient on impact (i.e., for $h = 0$).

	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Of which due to shock:				
	A. Log stock returns (bps)					
	Δs	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
FOMC day dummy	32.9***	4.59	9.84*	11.2**	7.18	18.4**
	(3.29)	(0.82)	(1.92)	(2.12)	(1.22)	(2.46)
Constant	-2.14	-0.62	-0.081	-0.60	-0.85	-1.44
	(-1.09)	(-0.65)	(-0.11)	(-0.59)	(-1.06)	(-1.07)
N	4182	4182	4182	4182	4182	4182
	B. Two-year yield changes (bps)					
	$\Delta y^{(2)}$	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
FOMC day dummy	-0.41	0.28	-0.80**	0.35**	-0.24	0.11
	(-0.68)	(0.88)	(-1.97)	(2.20)	(-1.40)	(0.44)
Constant	-0.028	-0.042	0.0059	-0.019	0.027	0.0082
	(-0.30)	(-0.74)	(0.10)	(-0.62)	(1.16)	(0.22)
	C. Ten-year yield changes (bps)					
	$\Delta y^{(10)}$	ω^g	ω^m	ω^{p+}	ω^{p-}	ω^{p+}, ω^{p-}
FOMC day dummy	-0.18	0.17	-0.41**	0.67**	-0.60	0.064
	(-0.29)	(0.87)	(-1.99)	(2.20)	(-1.33)	(0.11)
Constant	0.011	-0.025	0.0029	-0.037	0.070	0.033
	(0.11)	(-0.73)	(0.10)	(-0.62)	(1.12)	(0.40)

Table IA-8. FOMC dummy regressions (1994:09–2011:03 sample). The table reports regressions of yield changes and log stock returns on the FOMC day dummy for scheduled FOMC meetings. The sample period is from September 1, 1994 through March 30, 2011. See notes to Table II for further details. All coefficients are in basis points. t-statistics robust to heteroskedasticity are reported in parentheses.