Common shocks in stocks and bonds

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We propose a new approach to identifying economic shocks from asset prices. Our identification disentangles monetary news, growth news as well as pure risk-premium shocks on any day from the variation in the stock market and the Treasury yield curve. We use this approach to analyze news content of macroeconomic announcements and channels through which the Fed affects asset prices. We document a pronounced effect of the Fed on risk premiums that dominates the conventional monetary news channel. About 70% of the average positive stock returns earned over the FOMC cycle stem from the Fed-induced reductions in risk premiums. We further explain the puzzling fact that stocks *but not* bonds earn high returns on FOMC days. As bonds hedge growth risk in stocks, Fed-induced reductions in the value of the bond insurance premium offset any gains, making overall bond returns on FOMC days economically small. Overall, since the early 1980s, conventional monetary news accounts for 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 directly 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 the Treasury yield curve? More specifically, how important are monetary, growth, and risk-premium news for asset prices? While asset pricing models predict a tight link between the sources of variation in stocks and bonds, such link has been difficult to establish empirically. Correlations between stock 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).

Our goal is to reconcile these facts by decomposing the variation in the U.S. aggregate stock market and the Treasury yield curve into structural shocks which have an intuitive economic interpretation. We isolate growth news, monetary news, and two distinct shocks generating time-varying risk premiums, recognizing that stocks and yields are differentially exposed to those shocks.[1] For one, good news about real activity (positive growth news) raises both stock prices and yields, while 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 positive comovement 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 direction arise from bonds providing a

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

hedge for cash-flow risk in stocks. We refer to these shocks as the common premium and the hedging premium, respectively. Both risk-premium shocks work to affect stock prices in the same direction (positive shocks lower stock prices), but they have opposite effect 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 driving 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 and risk-premium shocks into an exposure that is common to stocks and bonds and the hedging component. 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 thus be exploited to isolate the risk-premium shocks.

We implement the above ideas via sign restrictions drawing on a large literature on structural vector autoregressions (VAR).[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 the Fed communication illustrates this point. The identification of monetary shocks typically relies on the timing of the Fed announcements

[2]See e.g., Faust (1998), Faust, Swanson, and Wright (2004), Uhlig (2005), Rubio-Ramirez, Waggoner, and Zha (2010), Arias, Caldara, and Rubio-Ramirez (2019), Ludvigson, Ma, and Ng (2019), as well as Fry and Pagan (2011) and Kilian and Lütkepohl (2017) for reviews of this literature.

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 update 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 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.

We apply the method to study the information content of macroeconomic and Fed announcements. 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 premium contribute to raising both stock and bond prices on FOMC days, with accommodating monetary news having a smaller but still significant effect. For stocks, risk-premium shocks generate nearly 70% of the average FOMC day returns, while monetary shocks account for another 25%. Importantly, 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 a decline in the value of 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

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

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. Our identification provides independent verification of those results as it does not involve assumptions about 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 similar to FOMC days. Although the common premium and monetary news 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 Fed-induced news, we study the content of the non-farm payroll releases to illustrate a similarly multidimensional nature of macroeconomic announcements, as initially highlighted by Boyd, Hu, and Jagannathan (2005). Our results show that non-farm payroll releases induce significant updates to investors' expectations about monetary policy. Specifically, while in contractions investors read non-farm payroll numbers as revealing information about the actual state of the economy, in expansions they view them primarily as news about the path of monetary policy.

Finally, we analyze the overall importance of different shocks for the dynamics of stocks and yields 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 (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, Bollerslev, Diebold, and Vega (2007) and Connolly, Stivers, and Sun (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, Engstrom, and Xing (2009), Bekaert, Engstrom, and Grenadier (2010), Burkhardt and Hasseltoft (2012), Campbell, Sunderam, and Viceira (2017), Campbell, Pflueger, and Viceira (2019), David and Veronesi (2013), Koijen, Lustig, and Van Nieuwerburgh (2017), Lettau and Wachter (2011), Song (2017)). Baele, Bekaert, and Inghelbrecht (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 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 (e.g., Matheson and Stavrev (2014), Cieslak and Schrimpf (2019), and Jarocinski and Karadi (2019)). We contribute to that literature in several ways. From the methodological standpoint, 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 (3-month Fed fund futures rate or 10-year yield, respectively) 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 between the common and the hedging premium. Jarocinski and Karadi (2019) and Cieslak and Schrimpf (2019) concentrate only on central bank communication in narrow event windows. Our objective, instead, is to understand the economic shocks driving stocks and bonds on any day over a long sample going back to the 1980s. We find that accounting for two dimensions in the risk premium is important for understanding the joint stock-bond dynamics.

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 and around non-farm payroll announcements. Section V analyzes the contributions of different shocks to the overall variation in stocks and yields, and studies the persistence of news effects 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

Asset prices (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 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)

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

[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.

where $\Psi(L)$ is the polynomial in the lag operator L, $\Psi(L) = \sum_{i=1}^{p} \Psi_i L^i$, and innovations 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 $\mu_F = A^{-1}(\mu_Y - (I - \Psi(L))a)$, with I identity matrix, $\Phi_i = A^{-1}\Psi_i A$, and $\nu_t = A^{-1}u_t$. The state vector can contain investors' beliefs about fundamentals, stochastic volatilities (uncertainty), or time-varying market prices of risk. We are only able to isolate shocks to time-varying second moments to the extent that such shocks affect asset prices via risk premia. Therefore, we do not explicitly model time-varying conditional volatility of the state vector.

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 structural, i.e., mutually uncorrelated, $\nu_t = \Sigma_F \omega_t$ with Σ_F diagonal matrix, and ω_t are unit-variance shocks, $Var(\omega_t) = I$. 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. We discuss the implications of the time-varying volatility of structural shocks by allowing Σ_F to change over time in Appendix A. 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 detail in Section III.

II.B. Model illustration

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 affine 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 factor 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 $\delta_m = 1$. 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 B. 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 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, which we further motivate in Section III. If $0 < \delta_g < 1$, then $B_s^g > 0$ and $B_n^g > 0$, i.e., growth news moves stocks and yields in the same direction. With $\delta_m = 1$, $B_s^m < 0$ and $B_n^m > 0$, i.e., monetary news moves stocks and yields in opposite 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 $B_n^\tau > 0$, in which case expected inflation shocks move stocks and yields in opposite direction and hence have an analogous effect to monetary news.

As one can view a stock as a long-term bond plus cash-flow risk, it is plausible that 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 discount 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-safety" 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

[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 $\Delta s_{t+1} \approx \kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t$.

shocks are priced with constant risk premiums. Then, shocks to the log 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, x_t^+, x_t^-. 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, the risk premiums inherit the respective exposures of stocks and bonds to g_t and m_t shocks via loadings B^g and B^m. 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^+ variable 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, and we 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.

[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 a 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 impacts on the yield curve, and the same impact 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).

Under the expectations hypothesis (EH), the effect of (a mean-reverting) shock to the short-rate should fade at long maturities. Indeed, under the EH, the long-term yield is the 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 $\frac{1}{n}\frac{1-\rho^n}{1-\rho} < 1$ 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 multivariate case (see Appendix C). 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. Absent 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 and restrictions on the $\tilde{A}$ matrix. Consequently, shocks that we identify are innovations to the information set of investors.

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. 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.

As we recover the structural shocks 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.

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 $\omega_t = \left(\omega_t^g, \omega_t^m, \omega_t^{p+}, \omega_t^{p-}\right)'$ 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 yields across maturities.

Restrictions on shocks to growth expectations. *Positive shocks to growth expectations raise stock 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 or price-consumption ratios) through the cash-flow and the discount-rate news channels. 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 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 of growth news 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, Elton, and Green, 2001; Fleming and Remolona, 2001; Gürkaynak, Sack, and Swanson, 2005b; Gürkaynak, Kisacikoglu, and Wright, 2018).[8]

[8] The results in Balduzzi, Elton, and Green (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

To further motivate the growth 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).[9] 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.[10] 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 the two-year yield (column (3)) by 25 bps ($t = 4.1$) 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 yield 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. *A monetary tightening shock depresses stock prices and raises yields. The effect on yields declines in strength with yield maturity.*

The monetary 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. This reaction reflects the discount rate effect: a drop in the risk-free component of the discount rate pushes stock and

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 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.

[9] 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., $\mathrm{Updt}_t(g_h) = F_t(g_h) - F_{t-1}(g_h)$. 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 ($h = 0$), $\mathrm{Updt}_t(g_0)$, 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.

[10] 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. In this and subsequent tables, $^{***}/^{**}/^{*}$ denotes significance at 1%/5%/10% level.

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 yield.[11] 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 the risk premiums. These are shocks to financial assets that are orthogonal to monetary and growth news. Although we are agnostic about the exact mechanism, 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,

[11] See Poole, Rasche, and Thornton (2002), Gürkaynak, Sack, and Swanson (2005a), Gürkaynak, Sack, and Swanson (2005b), Campbell, Evans, Fisher, and Justiniano (2012), Hanson and Stein (2015), Nakamura and Steinsson (2018).

the two-factor structure in risk premiums is key for jointly explaining the variation in stocks and the yield curve.

Risk-premium shocks. *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. Common premium shocks induce a negative comovement between yields and stocks and hedging premium shocks induce a positive comovement.*

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)).[12] 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.[13] 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. As indicated by Table I, expected inflation has a level effect on the yield curve (leaving its slope essentially unchanged) and an insignificant effect on the stock market. 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 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

[12] 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.

[13] 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 monetary and growth restrictions.

the high-frequency (daily in our application) variation in yields is small (Bekaert, Cho, and Moreno, 2010; 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 shocks to expected inflation should have a minimal impact on day-to-day variation in asset prices, which is the frequency we focus on.[14]

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 a given asset responds to different shocks; moving across rows describes how a given shock affects different assets. We impose three types of restrictions, all on

[14]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 the Taylor principle satisfied ($\delta_\tau > 1$), the effect of expected inflation shocks on the comovement of stocks and yields is analogous to that of 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.

the contemporaneous impact of structural shocks on innovations in asset prices: (i) *sign restrictions* that determine the direction in which a shock moves yields and stocks; (ii) *between-asset restrictions* that determine the relative effect of shock ω_i on the different elements of Y; and (iii) *within-asset restrictions* that determine the relative importance of different shocks for a given element Y_i.

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 growth ω^g and the hedging premium ω^{p+} shocks move stocks and yields in the same direction (first and third column of $\tilde{A}$), whereas monetary ω^m and common premium ω^{p-} shocks 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 at 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 the risk premium shocks, 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-asset 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 $\frac{(A_m^{(10)}\sigma_m)^2+(A_g^{(10)}\sigma_g)^2}{(A_{p+}^{(10)}\sigma_{p+})^2+(A_{p-}^{(10)}\sigma_{p-})^2} < 1$ for the ten-year yield. Those restrictions are consistent with the evidence on the properties of interest rate volatility (e.g., Cieslak and Povala, 2016). Appendix D provides a concise list of all restrictions.

III.C. Data and sample 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, Sack, and Wright (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 asset prices Y_t from a VAR(1) estimated on daily yield changes and stock returns, $z_t = \Delta Y_t = Y_t - Y_{t-1}$. We apply maximum likelihood on demeaned z_t. The lag length of one is determined using the Bayesian information criterion.[15]

To recover structural shocks ω_t, we start from the Cholesky decomposition of the variance-covariance matrix of reduced-form shocks u_t, $\Omega_u = PP'$, where P is a lower triangular matrix, $u_t = P\omega_t^*$, and ω_t^* denotes a set of uncorrelated shocks, $Var(\omega_t^*) = I$. Shocks ω_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

[15] We use log stock returns as opposed to changes of the log price-dividend ratio. Using Campbell-Shiller linearization return innovations are $\Delta s_{t+1} - E_t(\Delta s_{t+1}) \approx \kappa_1(pd_{t+1} - E_t(pd_{t+1})) + (d_{t+1} - E_t(d_{t+1}))$. 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, the noise stemming from the second term can be assumed negligible given the smooth dynamics of aggregate dividends. We verify that using either cum-dividend returns or capital gains leads to essentially identical stock returns decomposition. This is expected given that a regression of daily cum-dividend returns on daily capital gains in the S&P 500 index has the slope coefficient of 1.006, the intercept of -1 bps, and the $R^2 = 0.9989$.

a VAR. One can obtain observationally identical set of reduced-form shocks by finding an orthonormal rotation matrix Q 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, Waggoner, and Zha (2010) (see also Kilian and Lütkepohl (2017)). While there are many matrices Q leading to observationally equivalent innovations u_t, we are interested in the subset that satisfies the restrictions laid out in Section III.B. Denoting by $\mathcal{R}$ the set of rotation matrices for which $\tilde{A}(Q) = PQ'$ satisfies the restrictions, 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 our restrictions on which we base our subsequent analysis.

III.E. Dealing with model multiplicity

The identification approach using sign restrictions leads to model multiplicity, with 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 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 element-wise 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 MT solution generates nearly perfectly overlapping paths with the median taken across solutions. The 10th and 90th percentiles illustrate the uncertainty associated with the set identification, as opposed to estimation uncertainty coming from the uncertainty in the estimates of the reduced-form parameters. Estimation uncertainty is negligible compared to the model uncertainty, and we relegate the discussion of its role to the Appendix E (see in particular Appendix Figure IA-1).

To compare solutions, we study the correlations between shocks from the MT model and the other retained models. Correlations of the median of shocks across solutions with the MT shocks exceed 0.985 for all 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 (see Appendix Figure IA-2). This suggests that different solutions have similar implications for the evolution of structural shocks over time.

With Gaussian shocks, we do not explicitly model the time-varying second moments in asset prices, and identify shocks to volatility only to the extent that they affect expected returns. As we argue in Appendix A, stochastic volatility does not affect historical decompositions of asset returns into contributions of structural shocks. To additionally examine the stability of the shocks we identify, we reestimate the model on different subsamples, 1983–1997, 1998–2007, and 2008–2017. The first breakpoint in the late 1990s is when the stock-yield correlation changed sign from negative to positive; the second breakpoint at the end of 2007 accounts for the zero-lower-bound period.[16] We find that shocks identified over those

[16]While the zero-lower bound constrained the volatility at the very short-end of the yield curve, the two-year yield (shortest maturity we use) remained sensitive to news in that period (Swanson and Williams, 2014).

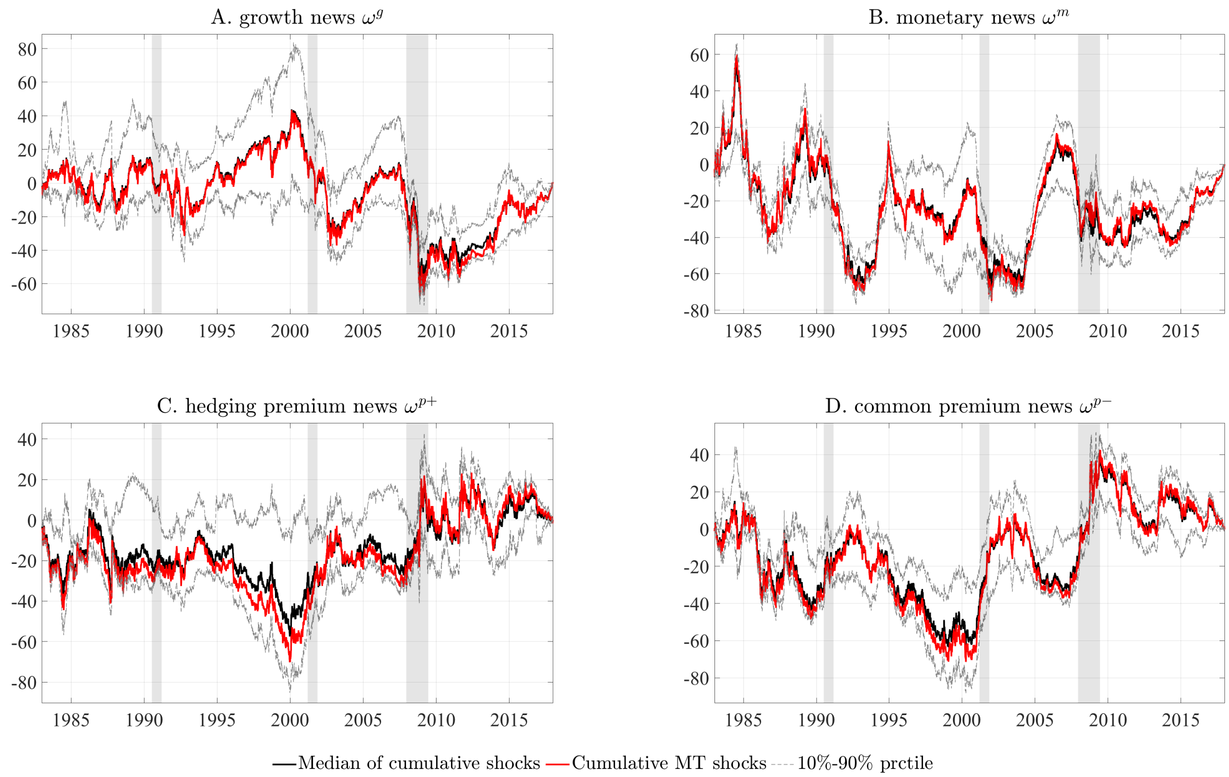

Figure 1. Paths of cumulative shocks. The figure presents paths of cumulative shocks for the MT solution as well as the median, 10th, and 90th percentile of cumulative shocks across retained solutions. Daily shocks are normalized to have zero mean and unit standard deviation over the 1983–2017 sample.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

subsamples are highly correlated with the respective full-sample estimates, and are situated closely on a 45-degree line against each other (Appendix Figure IA-3). In the following sections, we provide additional discussion of the robustness of our results to spliced-sample estimates, where we run separate estimations over subsamples.

III.G. 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:

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

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

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

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 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. Dissecting the content of the Fed and macroeconomic news events

The decomposition of asset prices into economic shocks allows us to analyze the content of major economic news events. The information revealed by policy and macroeconomic announcements can be complex. We start by exploring the drivers of asset prices on FOMC announcement days, over the full FOMC cycle, and the content of the commonly used measures of monetary policy surprises. We then extend the analysis beyond the Fed-related events to further document how macroeconomic announcements, in addition to providing news about the state of the economy, lead to significant updates of investors' beliefs about the path of monetary policy and risk premia.

IV.A. The Fed-induced news

In addition to the conventional monetary news, the policy transmission can also work via the information and the risk-premium channels. In the information channel, the Fed reveals information about economic fundamentals that markets did not have (the so-called information effect); in the risk premium channel, it influences the amount or the price of risk perceived by investors. Those channels map onto our decomposition of asset prices into monetary (ω^m), growth (ω^g), and risk premium news (ω^{p+}, ω^{p-}), allowing us to assess their relative importance.

[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.

IV.A.1. FOMC days

We first study the drivers of average stock returns and yield changes on scheduled FOMC announcement days. Lucca and Moench (2015) document that stocks earn high average returns in the 24-hour window before the scheduled FOMC announcements, but Treasury yield changes are indistinguishable from zero on average. While our decomposition applies to daily close-to-close returns, as opposed to pre-FOMC returns, daily returns capture most of the effect. We regress the overall log stock returns and yield changes as well as their historical decompositions (19) for each shock on the FOMC dummy that equals one on scheduled FOMC announcement days and zero otherwise:

$$z_t^j \text{ or } z_t^j(\omega_t^i) = \gamma_0 + \gamma_1 1_{t,\text{FOMC}} + \varepsilon_t. \tag{20}$$

For consistency with much of the recent literature, we first focus on the post-1994 sample, when the Fed started making public announcements of its decisions.[18]

Figure 2 reports the estimated γ_1 coefficients along with robust 95% confidence intervals. The coefficients measure the average change in the dependent variable on FOMC days compared to all other days. All coefficients in the graph are in basis points. By multiplying the coefficients for yield changes 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.

The first estimate in each panel of Figure 2 shows the average change in overall asset returns on FOMC days. Stock returns are significantly higher on FOMC days, on average by 27.5 bps ($t = 3.32$), than on other days. By contrast, yields are not materially changed: Two- and ten-year yields on average decline by about a half basis point (statistically insignificant). Subsequent estimates in each panel decompose the overall effect into contributions of individual shocks. All shocks contribute positively to stock returns, thus accumulating into a large overall effect. Monetary shocks ω^m and both risk-premium shocks, ω^{p+} and ω^{p-}, significantly raise stock returns by 7, 9, and 10 bps (all significant at the 10% level or better),

[18] Before 1994, there remains uncertainty about the timing of when the Fed decision reached financial markets (Thornton, 2005).

respectively. The growth news ω^g component is close to zero, suggesting that on average the FOMC days are not associated with systematically positive or negative news about the economy. Shock contributions to yields are mixed. Monetary news ω^m and the common premium shocks ω^{p-} reduce the ten-year yield by -0.3 and -0.8 bps, respectively, while the hedging premium shocks ω^{p+} raise it by 0.5 bps. The combination of these opposing effects leads to insignificant yield changes overall.

The final estimate in each panel of Figure 2 reports the joint contribution of the risk-premium shocks. For yields, the risk-premium shocks cancel each other such that their total impact is not statistically different from zero. For stocks, however, the risk-premium shocks account for more than two-thirds (68% (= 18.7/27.5)) of the average increase in returns on FOMC days. The positive sign means that FOMC days are associated with risk-premium declines that push stock prices higher.[19]

For robustness, we replicate the above analysis using spliced-sample estimates, combining shocks and historical decompositions estimated separately over the pre- and post-1997 sample. The results are quantitatively very similar to those above based on the full-sample estimates, with risk-premium shocks explaining more than 60% of the FOMC day effect in stock returns (Appendix Figure IA-4). In addition to the baseline results that rely on the MT solution, we also consider the role of model uncertainty and study the distribution of the γ_1 coefficients in regression (20) using all retained solutions. The significant impact of risk premium shocks (especially common premium ω^{p-}) and monetary easing shocks is a robust finding across solutions (Appendix Table IA-2).

Given that the FOMC day effect in stock returns emerges particularly strongly from the mid-1990s, it is useful to understand what has changed pre- and post-1994. Estimating regression (20) over the 1983–1993 period, stock returns are 19 bps (t = 1.82) higher on FOMC days compared to other days. Our decomposition reveals that this number continues to be driven by the risk-premium part, but now the common premium ω^{p-} shock is the only significant component, effectively accounting for the entire pre-1994 effect. Importantly, compared to 7

[19]In our identification positive risk-premium shocks lower stock prices (equation (14)). As we show in Section VI.B, those shocks comove positively with innovations to several measures of the equity risk premiums used in the literature.

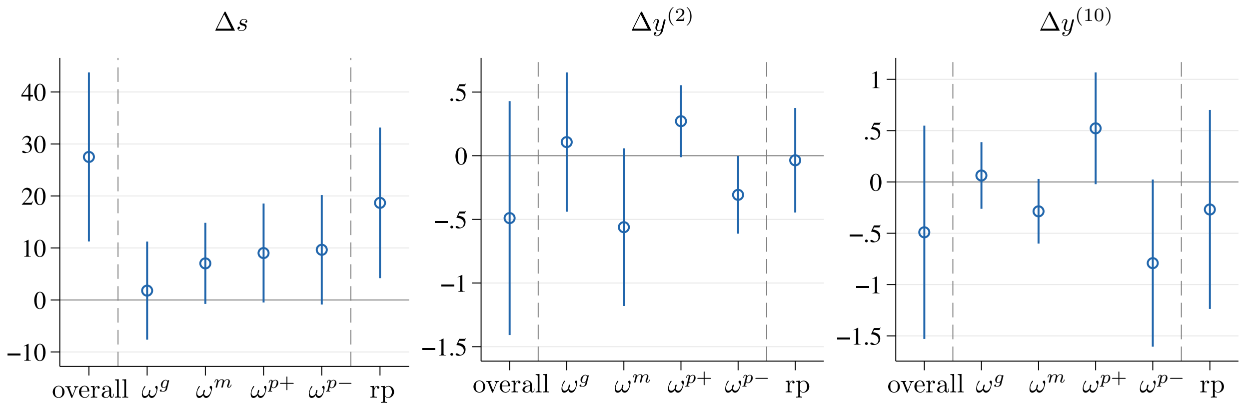

Figure 2. Stock returns and yield changes on scheduled FOMC announcement days. The figure reports the slope coefficients from regressions (20). All coefficients are in basis points. The first estimate in each panel represents the overall effect, i.e., the average change in stock returns (or yields) on FOMC days compared to all other days. For the next four estimates, the dependent variable is the historical decomposition (19) representing the part of the stock return (yield change) explained by a particular shock ω^i, $i = \{g, m, p+, p-\}$. Thus, coefficients across ω's sum up to the overall effect. The last estimate labelled "rp" separately reports the coefficient for the the overall risk-premium component (e.g., for stocks the dependent variable is $\Delta s(\omega^{p+}) + \Delta s(\omega^{p-})$, and analogously for yields). Regressions are estimated over the 1994–2017 sample (6053 days), covering 192 scheduled FOMC meetings. The spikes indicate 95% confidence intervals based on the standard errors robust to heteroscedasticity.

bps in the post-1994 sample, the effect of monetary news on stocks is estimated to be zero, thus explaining most of the reduction in the average stock returns on the FOMC days in the pre-1994 sample compared to the post-1994 sample. The details of the pre-/post-1994 comparison are provided in Appendix Figure IA-5. The increased contribution of monetary news from 1994 aligns with the view that, given the stability of inflation expectations, the Fed has eased more aggressively than what the public expected in that period (Cieslak, 2018; Bauer and Swanson, 2020).

IV.A.2. FOMC cycle

The FOMC day returns are part of a broader pattern of stock returns between scheduled FOMC meetings. CMVJ (2019) argue based on a series of facts that information from the Fed disproportionately arrives in "even weeks" in FOMC cycle time, i.e., weeks zero, two, four and six measured starting from the last scheduled FOMC meeting. They show that excess stock returns are on average significantly higher in the "even weeks," yet, similar to the FOMC days, the results are less clear for bonds.

In Table II, we revisit the baseline CMVJ regressions of stock returns and yield changes on even-week dummies, and separately for their shock-specific components. 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 0 and 10.2 bps ($t = 3.03$) per day higher in weeks 2, 4, and 6 of the FOMC cycle than they are in the other weeks.[20] Subsequent columns show that the result is largely driven by the common premium shocks ω^{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 week 0, while monetary news and hedging premium news ω^{p+} 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 ten-year yield (-0.46 bps decline with $t = 2$). However, shock-specific regressions reveal a negative and significant impact of the common premium shocks ω^{p-} across all even weeks, which parallels the estimates for stocks and implies a decrease in the Treasury premium. The negative coefficient for the week 2, 4, 6 dummy is reinforced by monetary shocks which push yields down (with marginal significance) in those weeks, suggesting that more news about monetary easing comes out in even weeks in FOMC cycle time. The monetary channel, however, is quantitatively only about a quarter of that of the risk-premium news.

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.

[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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Of which due to shock:				
A. Log stock returns (bps), $N = 6053$						
	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)
B. Two-year yield changes (bps), $N = 6053$						
	$\Delta y^{(2)}$	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)
C. Ten-year yield changes (bps), $N = 6053$						
	$\Delta y^{(10)}$	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)

Table II. FOMC cycle regressions. The table reports regressions of daily log stock returns and daily yield changes on the even-week dummies defined as in CMVJ (2019). All coefficients are in basis points, and regressions are estimated with a constant, which is suppressed in the output for brevity. In column (1), the dependent variable is the overall stock return or yield change. In columns (2)–(5), the dependent variables are the historical decompositions (19) of stock returns and yields changes into contributions of structural shocks. Column (6) separately reports the coefficients for the total risk premium component (e.g., for stock returns the dependent variable is $\Delta s(\omega^{p+}) + \Delta s(\omega^{p-})$). Regressions are estimated over the 1994–2017 sample, covering 192 scheduled FOMC meetings. t-statistics robust to heteroscedasticity are reported in parentheses.

IV.A.3. Measures of monetary policy surprises

The results so far demonstrate the average effect of different types of news on stock returns and yield changes on days that are likely to contain information from the Fed. A related approach studies responses of asset prices to various measures of monetary policy surprises. Gürkaynak, Sack, and Swanson (2005a, GSS) show how to decompose Fed announcements into an action and a communication component, which they refer to as the target and the path factors. The path factor is defined as news about the future short rate that is uncorrelated with current target shocks (i.e., with shocks to the current Fed's policy rate). Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018) argue that a large portion of path shocks is due to the Fed telegraphing information about growth, i.e., the information effect. Hanson and Stein (2015), instead, propose that they capture changes in the risk premium induced by the Fed. It is therefore informative to connect monetary surprises used in the literature to our structural decomposition in order to quantify the role of the conventional monetary news vis-a-vis the information and the risk-premium channels.

We use surprises from Swanson (2018) who updates the original GSS series through October 2015 and extends the GSS methodology to include large scale asset purchases (LSAP) shocks. GSS/Swanson identification exploits movements in the shortest maturity interest rates from the Fed fund futures and Eurodollar contracts (as well as 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 years and above, and no event-timing restrictions.

In Table III, we project the target, path and LSAP surprises on the four structural shocks we identify. We report results using scheduled FOMC announcements post-1994 as well as all FOMC announcements (including unscheduled) over the 1991:7–2015:10 period considered by Swanson (2018). Columns (1) and (3) show that the monetary shock in our decomposition is the only variable that has explanatory power for the target. In contrast, the path factor in columns (2) and (4) is significantly related to all variables except the hedging premium ω^{p+}, implying that path shocks aggregate different channels through which the Fed communication affects asset prices. All significant loadings are positive, i.e., a negative path shock can occur because of negative fundamental information revealed by the Fed, news about monetary easing, or news that reduces the risk premium. In terms of economic significance, the monetary component is the largest, followed by the common premium ω^{p-}, and then by the growth news.[21]

[21]Those results help understand the finding of Gürkaynak, Sack, and Swanson (2005a) that path surprises have a weak effect on stocks but a strongly significant effect on Treasury yields, which we confirm using scheduled meetings over the 1991–2007 sample, i.e., excluding the zero-lower bound period. Suppose we observe a negative path surprise. All structural shocks (growth, monetary, and common 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.

	(1)	(2)	(3)	(4)	(5)
	all meetings 1991:7-2015:10		scheduled meetings 1994–2015:10		2009–2015:10
	Target	Path	Target	Path	LSAP
ω^g	0.052	0.170*	0.100	0.256***	0.108
	(0.50)	(1.86)	(1.01)	(2.84)	(0.88)
ω^m	0.563***	0.375***	0.396***	0.517***	0.027
	(4.67)	(3.83)	(3.83)	(6.53)	(0.17)
ω^{p+}	0.011	0.010	0.008	-0.064	-0.338**
	(0.16)	(0.16)	(0.11)	(-0.97)	(-2.22)
ω^{p-}	-0.044	0.361***	-0.011	0.352***	0.715***
	(-0.63)	(5.32)	(-0.12)	(4.53)	(3.13)
R^2	0.34	0.30	0.18	0.46	0.68
N	213	213	175	175	55

Table III. Monetary policy surprises. The table reports regressions of GSS/Swanson surprises on shocks obtained using our identification. Columns (1) and (2) use all meetings (scheduled and unscheduled) over the 1991:7–2015:10 period, columns (3) and (4) use only scheduled meetings over the 1994–2015:10 period. Regression coefficients are standardized. *t*-statistics robust to heteroscedasticity are reported in parentheses.

Given that post-2008 many Fed announcements involve unconventional policies, in column (5), we separately report results for the LSAP shocks. The sample starts in 2009 when the Fed first launched quantitative easing. Following Swanson (2018), we normalize the LSAP shock so that its positive value implies interest rate increases. The estimates indicate a sizeable risk-premium effect, with the common premium 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-} shock is robust to omitting the most powerful announcement on March 18, 2009 (albeit the coefficient drops to 0.47). The significance of the hedging premium ω^{p+} is instead entirely driven by this single event. These results agree with the interpretation that LSAP worked primarily through reducing the risk premiums on stocks and long-term bonds rather than by affecting the expectations of the future policy stance.

Overall, the analysis of monetary policy surprises agrees with the asset price decompositions on FOMC days and over the FOMC cycle by highlighting significant Fed-induced changes to the risk premium, and a relatively smaller but still significant role for the information effect. It also demonstrates that common measures of monetary policy surprises are a combination of economically distinct structural shocks.

IV.B. News content of the non-farm payroll announcements

Macroeconomic news is another important category of events that induce sizeable asset price reactions. The difficulty in interpreting those reactions lies in the fact that, in addition to beliefs about the state of the economy, upon macro announcements investors also update their beliefs about monetary policy and/or perceptions of risk. Boyd, Hu, and Jagannathan (2005) show that announcements of rising unemployment are bad news for stocks in contractions but are actually good news for stocks in economic expansions. Law, Song, and Yaron (2018) document that sensitivity of stocks to macroeconomic news varies systematically over the business cycle, and is particularly high when the economy is below potential.

To disentangle these effects, we study how investors update beliefs over the business cycle in reaction to incoming non-farm payroll data. We focus on the non-farm payroll (NFP) announcements, as it is the most closely watched piece of macroeconomic news in the US (Andersen, Bollerslev, Diebold, and Vega, 2007). We construct NFP surprises (actual − expected) over the 1985:2–2017 period, using market participants' expectations of NFP before the announcement (with positive surprise meaning good news).[22] Following Law, Song, and Yaron (2018), we describe the state of the economy by the size of the unemployment rate gap, Gap = −(Current unemployment rate − Natural rate of unemployment).[23] High values of the Gap variable imply that the economy is above potential (e.g., Gali, Smets, and Wouters, 2011). We distinguish three states of the economy (bad/neutral/good times) by splitting the values of the Gap into terciles of sample realizations. We then regress the announcement-day asset price changes onto six dummy variables reflecting the full set of interactions between NFP announcement dummies (B=bad/G=good NFP news) and unemployment gap dummies (B=bad/N=neutral/G=good times):

$$z_t^j \text{ or } z_t^j(\omega_t^i) = \sum_k \beta_k 1_{t,k} + \varepsilon_t, \quad k = \{\text{BG, BN, BB, GG, GN, GB}\}. \tag{21}$$

[22] The start of the sample is dictated by the availability of NFP forecasts. Before 1997, we use forecasts from Money Market Services and from 1997 onward from Bloomberg.

[23] Current unemployment is the real-time civilian unemployment rate obtained from the Federal Reserve Bank of Philadelphia. The natural rate of unemployment (NROU) is from Federal Reserve Bank of St. Louis FRED database.

The first letter in subscript k indicates the type of NFP news and the second—the overall state of the economy, e.g., 1_{BG} is a dummy variable for bad NFP news coming out in good times. We estimate the regressions separately for stock returns, 2- and 10-year yield changes, as well as their components corresponding to each structural shock. The slope coefficients β_k in (21) measure the average stock return (yield change) conditional on bin k. Figure 3 presents β_k estimates for stock returns; for brevity, we relegate the results for yield changes to Appendix Figure IA-6. The first coefficient in each subplot is the overall average return; subsequent four coefficients decompose the overall effect into contributions of structural shocks; the last estimate is for the overall risk-premium component.

The upper panels of Figure 3 (BG, BN, BB) demonstrate the ambiguous response of stocks to bad NFP news. Specifically, while bad NFP news leads to negative stock returns in bad and neutral times (BN and BB), bad NFP news in good times (BG) induces *positive* stock returns (30 bps on average), as initially documented by Boyd, Hu, and Jagannathan (2005). The subsequent decomposition reveals that, while the impact of growth news is negative, the positive stock market response in the BG panel can be entirely explained by investors updating beliefs about monetary policy toward an easier stance. In good times, communication by the Fed makes tightenings well anticipated. However, when bad NFP news arrives, investors perceive it as a signal that the tightening cycle would end. Indeed, the negative reaction of the 2-year yield due to the monetary news in the BG state confirms that investors expect monetary policy to ease on bad NFP news in good times (Appendix Figure IA-6 panel BG). Moving from the left to the right panel in the first row of Figure 3, the effect of monetary news weakens in neutral and bad times, making the effect of bad NFP news on stocks more direct (panels BN and BB): stocks earn negative returns as investors revise downward their beliefs about growth.

The bottom panels of Figure 3 (GG, GN, GB) illustrate the effect of good NPF news. The negative effect of monetary news on stocks is visible when good NFP news arrives in good and neutral times (panels GG and GN). These are the times when the prospect of the Fed's tightening dampens the positive NFP news. This negative offsetting effect of monetary news tapers off when the economy weakens, with good NFP news in bad times (panel GB) having on average a positive effect on stocks.

Finally, the combined impact of the risk-premium news on stocks is insignificant across the six scenarios, and hence one might conclude that risk premia do not move on NFP news.[24] The common and hedging premium shocks can, however, have a distinct and individually large effect. In particular, good NFP news in bad times (GB) reduces the hedging premium (ω^{p+}) and increases the common premium (ω^{p-}) in stocks. To the extent that the two risk-premium shocks reflect a time-varying compensation for exposures to growth and monetary news, respectively, this result has an intuitive interpretation: Good NFP news in bad times reduces uncertainty about the real economy (hence ω^{p+} shocks push stocks up) but it also increases the uncertainty about discount rates as it may signal that an easing cycle would end (hence ω^{p-} shocks reduce stock prices). The reaction of Treasury yields is consistent with this interpretation, with both risk-premium shocks increasing the 10-year yield on bad NFP news in good times (Appendix Figure IA-6, panel GB).

V. Shocks in stocks and yields since the early 1980s

V.A. Variance ratios

Extending the analysis beyond the announcement events, we want to understand the overall amount of variation in yields and stock returns induced by different economic shocks over the last 35 years. We compute the variance ratios to describe the fraction of an asset's variance attributed to a structural shock as

$$VR_d^{j,i} = \frac{Var(u_t^j|\omega_t^i)}{Var(u_t^j)}, \tag{22}$$

where u_t^j is the reduced-form (daily) innovation to asset j, ω_t^i is the structural shock i, $Var(u_t^j|\omega_t^i)$ is the variance of innovation j induced by shock ω_t^i, and $Var(u_t^j)$ is the overall variance of innovation j. Since ω_t shocks are orthogonal, we have $\sum_{i=1}^4 VR_d^{j,i} = 1$. We

[24]For example, Boyd, Hu, and Jagannathan (2005) find an insignificant response of risk premium to bad news in contractions.

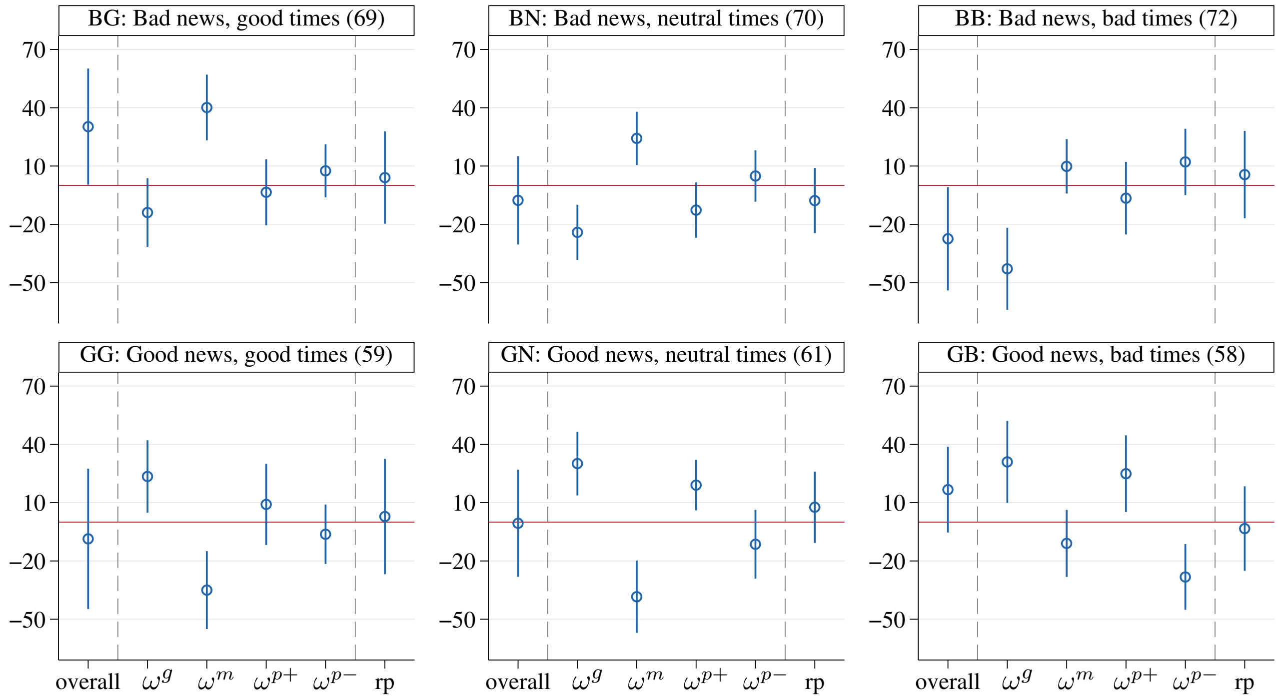

Figure 3. Stock returns on non-farm payroll announcement days. The figure reports average stock returns and their decompositions into contributions of structural shock on NFP announcement days, conditional on the type of news and the state of the economy. All numbers are in basis points. Good/Bad NFP news corresponds to the positive/negative NFP surprises (actual less expected NFP). The state of the economy (Good/Neutral/Bad times) is measured using the terciles of the Gap variable, Gap = −(Current unemployment − Natural rate of unemployment), with Gap in top tercile indicating good times. The estimates are obtained as β_k coefficients from regression (21), $k = \{\text{BG, BN, BB, GG, GN, GB}\}$. Each subplot combines estimates of β_k for a given k from six regressions, using a different dependent variable each. The sample period is 1985:2–2017, with 389 NFP announcements for which we have both survey and actual numbers, excluding announcements that fall on a holiday. Before 1997, NFP surprises are from Money Market Services, and from 1997 onward from Bloomberg. In parentheses, we report the number of NFP announcements falling into bin k. The spikes indicate 95% confidence intervals based on robust standard errors.

construct the variance ratios for the full sample (1983–2017) and for three subsamples, 1983–1997, 1998–2007, and 2008–2017. The split dates in 1997 and 2007 demarcate periods that are likely to represent different economic and monetary policy environments, where one can expect the volatility of the structural shocks to have changed.

Figure 4 displays the variance ratios for stock returns and yield changes.[25] In interpreting the graph, it is important to distinguish between assumptions and results. While we impose monotonicity restrictions across yields, our identification 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, different 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.

Focussing on the 1983–2017 sample in Panel A of Figure 4, about 80% of variation in the two-year yield comes from monetary and growth news, in about equal proportions. By contrast, monetary and growth news accounts for just below 20% of the variation in the ten-year yield, with more than 80% explained by the risk-premium shocks. Risk-premium shocks also constitute nearly 60% of the variation in stocks. Looking at different yields, the rapidly declining effect of monetary news across maturities is consistent with the view that these shocks do not have a major effect on long-duration assets. The cross-sectional impact of growth news is relatively more persistent at short and intermediate maturities, with the five-year yield responding only slightly less than the two-year yield.

Comparing different subsamples, the contribution of monetary news to asset prices generally declines over time, being the lowest in the post-2007 period, in line with the Fed's increased reliance on unconventional measures in recent years. However, the most pronounced change over time pertains to the role of the common premium shocks ω^{p-}, which explain nearly 50% of stock return variance before 1998, dropping to 30% in the 1998–2007 period, and to below 10% after 2007. This is accompanied by an increased contribution of the hedging premium shocks ω^{p+}. Given that the common premium induces a negative comovement of stocks and yields, while the hedging premium induces a positive comovement, those shifts help clarify the change in the stock-yield comovement from negative to positive in the late 1990s. Campbell, Pflueger, and Viceira (2019) argue that risk premia played the main role in generating the change in the stock-bond comovement, as bonds switched from risky to safe

[25] Figure 4 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-7. Additionally, Appendix Figure IA-7 quantifies the amount of uncertainty in these estimates stemming from the set identification.

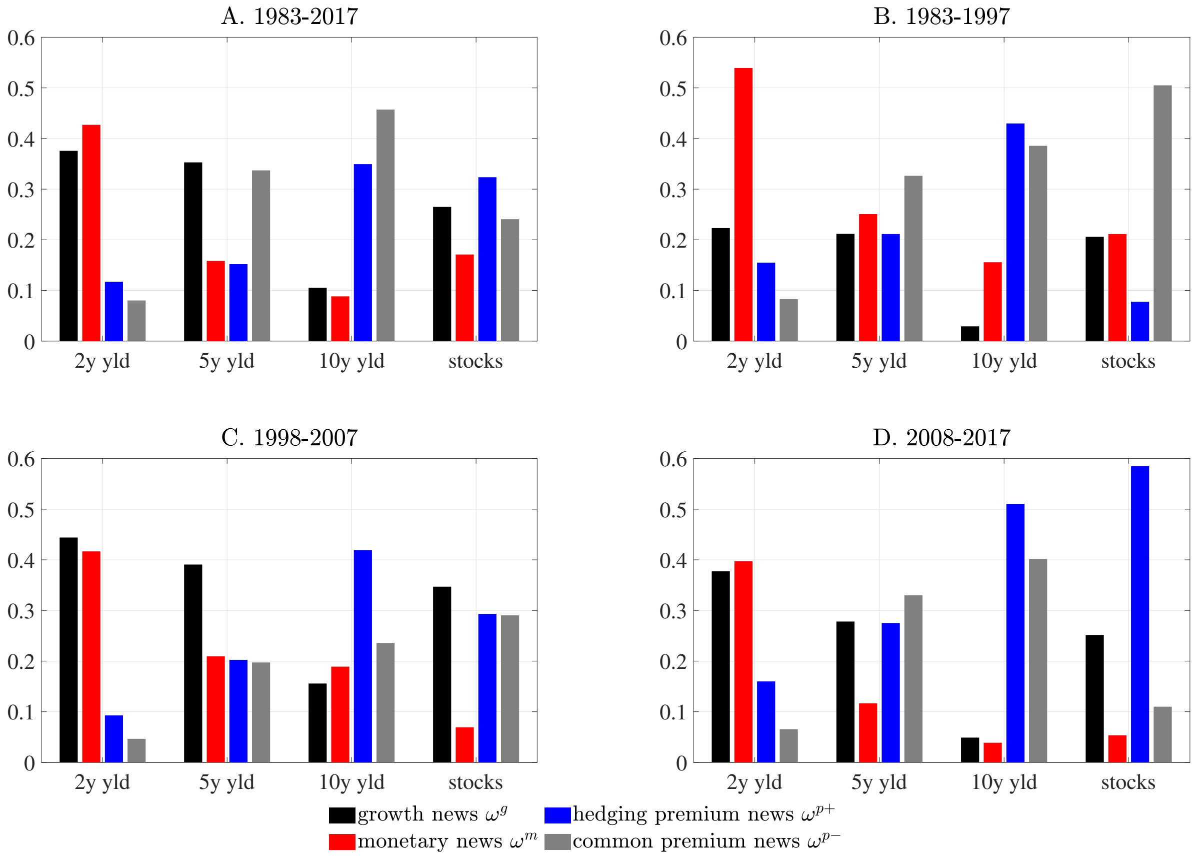

Figure 4. Variance decompositions. The figure presents variance decompositions of innovations in daily yield changes and stock returns into structural shocks. Structural shocks are obtained from the MT solution. The bars show the fraction of variance explained by each structural shock. Panel A reports full-sample estimates over the 1983–2017 period. Panels B through D are based on separate estimates for subsamples.

assets in the last two decades. Our results agree with this interpretation. While we allow both sources of risk-premium shocks to be present at all times, the variance ratios suggest that the risk-premium movements from the late 1990s primarily reflect time-varying compensation for growth news as opposed to discount-rate news, consistent with the increased hedging properties of bonds.

V.B. Persistence of the news effects

Variance ratios illustrate the amount of variance due to different structural shocks, but do not speak to the persistence of the effect that those shocks have on asset prices over time. To study the dynamic effect, we use the local projections approach of Jordà (2005) by regressing multihorizon yield changes and log stock returns on the vector of structural shocks, ω_t:

$$Y^j_{t+h-1} - Y^j_{t-1} = \alpha_h + \beta^{j\prime}_h \omega_t + \varepsilon_{t-1,t+h-1}. \tag{23}$$

Horizon h is in business days. The coefficient $\beta^{j,i}_h$ measures the impact of a one-standard-deviation shock in ω^i_t on a h-day yield change or stock return. Tracing out $\beta^{j,i}_h$ as a function of h, we obtain the cumulative impulse-response functions.[26]

Figure 5 plots the impulse responses for horizons up to three years (756 business days) over the 1983-2017 sample.[27] 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 5, we see how a particular shock impacts different assets. Importantly, our identification assumptions only restrict contemporaneous effects on impact ($h = 0$), leaving responses for $h > 0$ unconstrained. The on-impact responses 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 at shorter maturities, and stocks down. The effect of a one-standard-deviation monetary shock on the two-year yield is 3.6 bps on impact and increases up to 8 bps at about two-year horizon.[28] For assets other than the two-year yield, the effects of

[26]The full specification of Jordà (2005) controls for the level of Y_{t-1}, i.e., $Y^j_{t+h-1} - Y^j_{t-1} = \alpha_h + \beta^{j\prime}_h \omega_t + \delta'_h Y_{t-1} + \varepsilon_{t+h-1,t-1}$. Including those controls leads to almost identical results as (23); therefore, we report results of the parsimonious version with $\delta_h = 0$. When $h = 0$, regression (23) delivers R^2 (essentially) equal to unity 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 obtain structural shocks.

[27]For robustness, we also construct the impulse responses using shocks estimated over the 1998–2017 sample. The results, reported in Appendix Figure IA-8, are similar to those based on the full sample.

[28]This magnitude is in line with the estimates based on Kuttner's surprises (Kuttner, 2001). 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, however, are based on all dates, as opposed to the FOMC meeting dates for which Kuttner's surprises are available. The humped-shaped response is consistent with the evidence that investors' short-rate expectations have a sticky and extrapolative component, and thus adjust slowly to monetary news (Cieslak, 2018; Brooks, Katz, and Lustig, 2019).

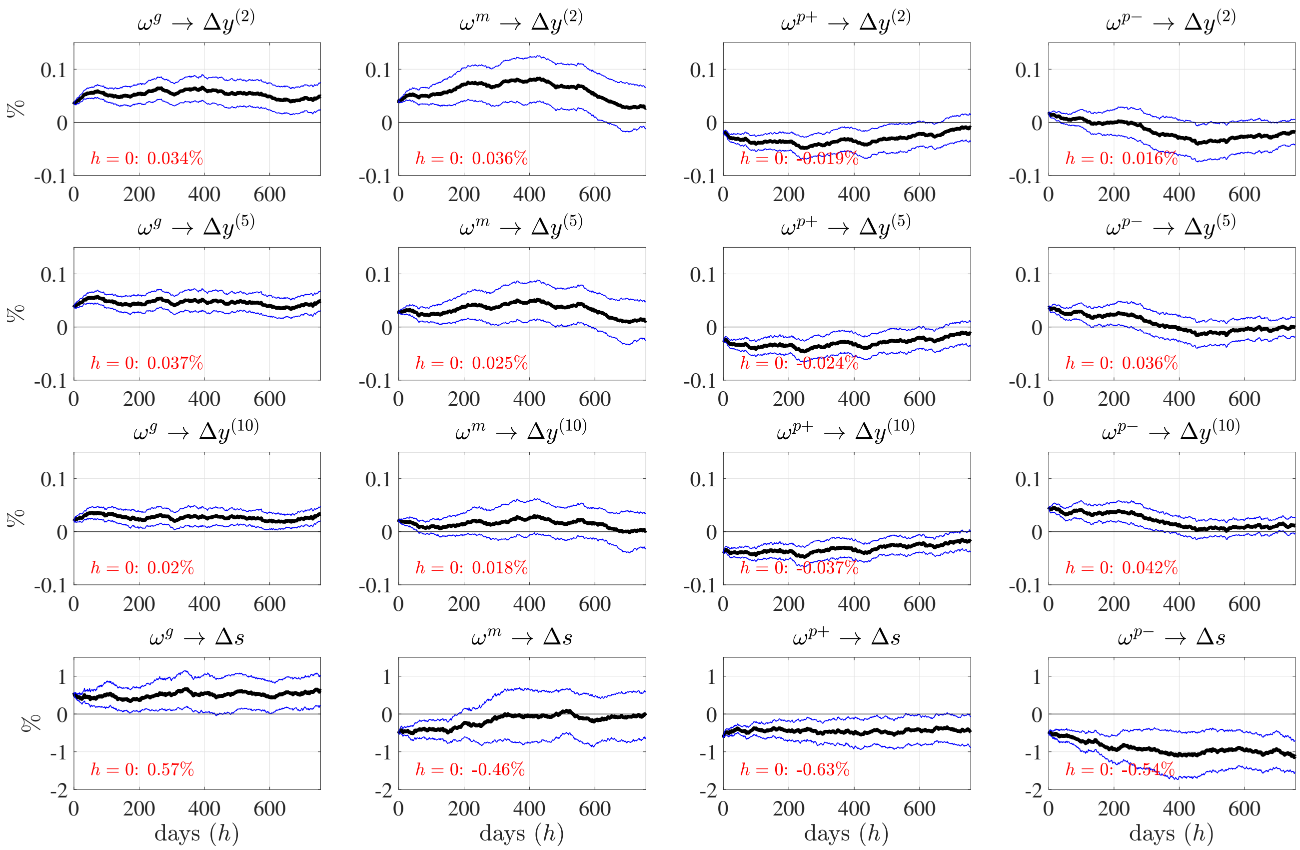

Figure 5. Cumulative impulse-response functions. The figure presents responses of yield changes and stock returns to structural shocks up to maximum horizon of three years (756 business days). Shocks are measured in units of standard deviation. Yield changes and stock returns are in percent. The thick line traces out the coefficients $\beta_h^{j,i}$ from regression (23). A coefficient of 0.1 implies an asset response of 0.1% 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 numbers in the bottom left corner of each graph report the coefficient on impact (i.e., for $h=0$). The sample period is 1983–2017.

monetary shocks mean-revert within about a year. The hedging premium shocks ω^{p+} have a relatively persistent effect on all assets, while the common premium shocks ω^{p-} impact mostly the long-maturity yields and stocks. The effect of ω^{p-} on stocks accumulates up to -1.16%, and its effect on the ten-year yield remains stable for about a year and becomes insignificant afterwards.

VI. Validity of identified shocks

This section discusses the validity of our identification by relating it to the observables that one expects to be sensitive to shocks we aim to identify.

VI.A. *Survey growth forecasts*

Survey forecast of the real GDP growth are highly sensitive to growth news. We thus study the relationship between our growth shocks and the real GDP growth forecast updates in the BCEI survey. For comparability, we sum daily ω^g shocks over the last k months, and similarly cumulate monthly survey forecast updates over the same k-month period. Figure 6 superimposes the two series, showing a close comovement between survey updates and identified growth shocks (for survey forecast horizon one quarter ahead $h = 1$ and $k = 3$ months). Appendix Figure IA-9 presents an analogous plot for $k = 12$ months.

Forecast updates in the survey do not have a structural interpretation as, in addition to growth shocks, they also reflect feedback effects between different structural factors driving expectations about the economy. Therefore, in Table IV, we regress forecast updates on all shocks from our identification to see whether we recover economically meaningful relationships.[29] The regressions are estimated for survey horizons from the current quarter ($h = 0$) to three quarters ahead ($h = 3$). The signs of the regressions coefficients have an intuitive interpretation. Survey growth forecasts update positively with the growth shocks ω^g, in line with the high correlation visible in Figure 6. Positive monetary news ω^m leads to significant growth expectations downgrades after a couple of quarters, as predicted by the standard monetary channel.[30] Finally, increases in the risk premium ω^{p+}, ω^{p-} are also associated with downgrades to growth expectations, consistent with the view that risk premia play a causal role for the real economy (e.g., Christiano, Motto, and Rostagno, 2014). Overall, these results support our proposed interpretation of shocks we recover.

[29] Our identification imposes that shocks are orthogonal at the daily frequency over the 1983–2017 sample. When converting shocks to a lower 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-4).

[30] The negative relationship holds except for the nowcast ($h = 0$). The positive coefficient on the nowcast (marginally significant) suggests the presence of an information effect (Nakamura and Steinsson, 2018; Campbell, Evans, Fisher, and Justiniano, 2012), i.e., monetary tightening signaling a better state of the economy than what the public expected.

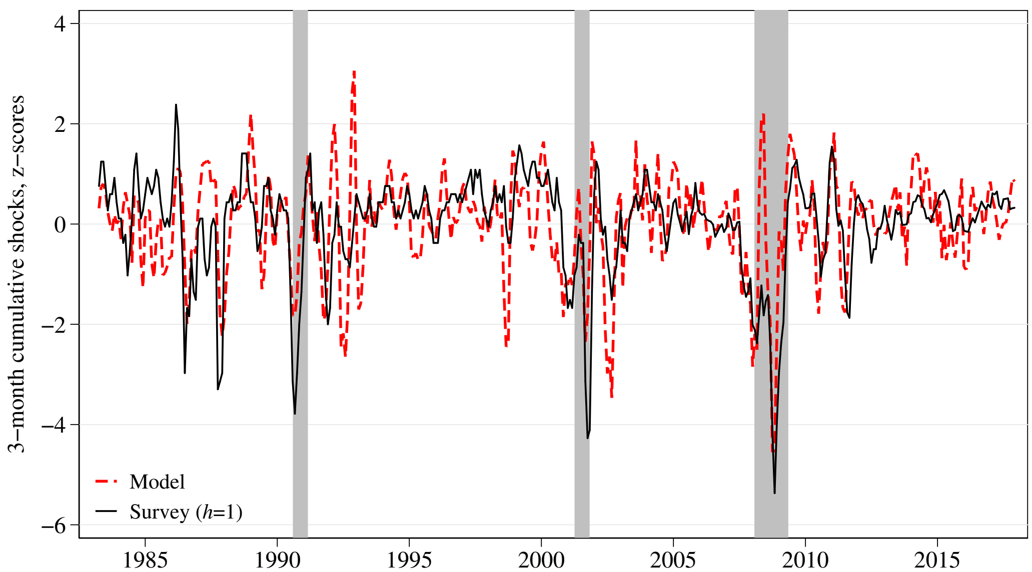

Figure 6. Comparison of model-based growth shocks with survey forecast updates for the real GDP growth. The figure superimposes growth shocks from the model with the forecast updates of real GDP growth expectations from the BCEI survey. The shocks and survey updates are cumulated over a 3-month period. Survey updates are for one quarter ahead ($h = 1$). Both variables are standardized to have zero mean and unit standard deviation.

	(1) $h = 0$	(2) $h = 1$	(3) $h = 2$	(4) $h = 3$
$\sum_{3\text{mth}} \omega^g$	0.436***	0.472***	0.393***	0.282***
	(7.08)	(7.52)	(4.66)	(3.71)
$\sum_{3\text{mth}} \omega^m$	0.118*	-0.129*	-0.360***	-0.415***
	(1.71)	(-1.72)	(-4.05)	(-4.74)
$\sum_{3\text{mth}} \omega^{p+}$	-0.251***	-0.255***	-0.211***	-0.120*
	(-2.95)	(-3.42)	(-2.84)	(-1.77)
$\sum_{3\text{mth}} \omega^{p-}$	-0.198***	-0.385***	-0.385***	-0.264***
	(-3.21)	(-5.70)	(-4.58)	(-2.89)
R^2	0.41	0.48	0.39	0.24
N	417	417	417	417

Table IV. Survey updates of the real GDP growth expectations. The table reports regressions of the real GDP growth expectations updates from the BCEI survey on shocks obtained with our identification scheme. Model-based 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 period 1983–2017. Slope coefficients are standardized with left- and right-hand side variables measured in z-scores. Newey-West t-statistics with 4 lags are reported in parentheses.

VI.B. Bond and equity risk-premium proxies

To assess the validity of our identification of the 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 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.

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 in bond and equity premiums are essentially uncorrelated,[31] demonstrating the challenge of jointly explaining the variation in risk premiums on stocks and bonds. Appendix Table IA-3 tabulates correlations across all variable pairs.

Our identification assumes that positive common premium shocks ω^{p-} increase the risk premiums on stocks and bonds, whereas positive hedging premium shocks ω^{p+} 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 listed above do not imply (nor are constructed under the assumption) that risk premiums are uncorrelated with the fundamentals, and thus, similar to survey updates above, their innovations do not have a structural interpretation. It is thus of interest to study how much of variation in the risk premium measures is explained by ω^{p+} and ω^{p-} alone.

Table V 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

[31] An exception is the correlation between $\widehat{cf}$ and the 2–3-month forward equity premium from Martin (2017) which reaches negative -25% estimated over the 1996–2012 sample.

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 variable in economic terms. The loadings have the expected signs moving bond risk premiums in opposite directions.

Table VI presents a similar analysis for the equity risk premium. There is significant heterogeneity across the equity risk premium measures, as evidenced by their weak correlation.[32] In Panel A, we use data from Martin (2017), available daily for the 1996–2012 sample, to calculate forward equity premiums for different maturities. 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-}, which is consistent with the increased role of hedging premium shocks from the late 1990s. The explanatory power of the model-based shocks for innovations in the forward premiums declines with 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. Turning to the KP and CAY variables in Panel B of Table VI, 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 agree with the view that the risk premium in the equity market is countercyclical, as well as that the monetary tightening increases the equity premium (Bekaert, Hoerova, and Duca, 2013). However, the results also suggest that a non-negligible fraction of variation in the risk premium on stocks stems from pure risk-premium shocks.

[32]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-3).

	$\widehat{cf}$ 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 V. Innovations to the 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.

VI.C. Monetary shocks

Section IV.A.3 shows that monetary shocks ω^m are positively and significantly related to monetary policy surprises used in the literature. In addition, if our approach correctly picks up monetary news, we expect the variance of monetary shocks ω^m to be higher on days with key monetary policy announcements compared to other days. In Table VII, we regress absolute values of each shock on the FOMC dummy. 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.[33] 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. 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

[33]Unscheduled FOMC announcements are usually interpreted as the Fed's response to other (unexpected) news events (e.g., Bernanke and Kuttner, 2005), and thus may not reflect monetary news. We also omit the post-2008 period, when the Fed launched an array of unconventional policy measures that affected asset prices through multiple channels.

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 VI. Innovations to the 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-5. 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 a 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.

significantly different on FOMC days from other days. As a non-negligible portion of the Fed communication happens outside of regularly scheduled FOMC meetings (and thus affects the

	(1)	(2)	(3)	(4)
	$\lvert\omega^g\rvert$	$\lvert\omega^m\rvert$	$\lvert\omega^{p+}\rvert$	$\lvert\omega^{p-}\rvert$
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

Table VII. FOMC dummy regressions. The table reports regressions of model-based shocks on the FOMC announcement day dummy for scheduled FOMC announcements. The dependent variables are absolute values of 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 heteroscedasticity are reported in parentheses.

regression intercept), the coefficient in column (2) is a conservative measure of the amount of monetary news on FOMC days.

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

VII. Conclusions

We propose a new approach to analyzing the sources of variation in asset prices. We exploit the fact that mainstream asset pricing models have a structural VAR representation. Economically interesting shocks can thus be uncovered from the reduced-form VAR dynamics of asset prices combined with restrictions on how shocks affect those prices. We impose intuitive restrictions on how shocks to investors' expectations about monetary policy, shocks to growth expectations as well as pure risk-premium shocks affect the joint dynamics of the stock market and the Treasury yield curve across maturities. We use our identification to study the drivers of stock and bonds around main economic events, and quantify the importance of the 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. Stability

This appendix discusses the implications of time-varying volatility of structural shocks for our identification. Figure IA-3 presents shocks estimated over the 1983–2017 versus different subsamples, showing that they are highly correlated. The goal of this appendix is to provide additional interpretation of these results.

Suppose that the true structural model is

$$Y_{t+1} = \mu + \Psi Y_t + A\Sigma_t \omega_{t+1}, \tag{IA.24}$$

where A is the true contemporaneous structural response matrix, Σ_t is the conditional volatility of structural shocks at time t (diagonal matrix with σ_t^i on the diagonal), and ω_t are iid shocks with $Var(\omega_t) = I$. The reduced-form innovations in asset prices are $u_t = A\Sigma_t\omega_t$. We want to assess the effect of applying our identification that assumes constant volatility, when the true model is (IA.24). Intuitively, the shocks we recover (denoted $\tilde{\omega}_t$ below) are not iid but have time-varying volatility.

For illustration, we consider a simple example with two regimes for Σ_t, but the intuition extends to more general dynamics of Σ_t. Assume the full sample has N observations, with $\Sigma_t = \Sigma_1$ for the first N_1 observation (subsample 1, $t \in \{1, ..., N_1\}$), and $\Sigma_t = \Sigma_2$ for the next N_2 observations (subsample 2, $t \in \{N_1 + 1, ..., N\}$), where $N_1 + N_2 = N$. We observe the reduced-form innovations in asset prices u_t. If we know the true value of $A\Sigma_t$, we can back out the structural shocks as $\omega_t = (A\Sigma_t)^{-1}u_t$. With two volatility regimes, $\omega_t = (A\Sigma_1)^{-1}u_t$ for $1 \le t \le N_1$ and $\omega_t = (A\Sigma_2)^{-1}u_t$ for $N_1 + 1 < t \le N$.

Let us now consider what happens if we recover shocks using a constant covariance matrix of reduced-form innovations u_t calculated over the full sample. The reduced-form covariance matrix of innovations in subsample i is $\Omega_i = A\Sigma_i\Sigma_i'A'$, $i \in \{1, 2\}$. Thus, the variance-covariance matrix of reduced-form shocks computed over the full sample is $\Omega = \frac{N_1}{N}\Omega_1 + \frac{N_2}{N}\Omega_2 = A(\frac{N_1}{N}\Sigma_1\Sigma_1' + \frac{N_2}{N}\Sigma_2\Sigma_2')A'$ and we define

$$\Sigma\Sigma' = \frac{N_1}{N}\Sigma_1\Sigma_1' + \frac{N_2}{N}\Sigma_2\Sigma_2'. \tag{IA.25}$$

$\Sigma\Sigma'$ can be viewed as the weighted average of the true conditional variances of structural shocks, with $\Omega = A\Sigma\Sigma'A'$. Thus, by imposing a constant conditional volatility, we recover $\tilde{\omega}_t = (A\Sigma)^{-1}u_t$ for $1 \le t \le N$ with sample variance of $\tilde{\omega}_t$ normalized to unity $\widehat{Var}(\tilde{\omega}_t) = I$. The relationship between $\tilde{\omega}_t$ shocks and the true ω_t is

$$\tilde{\omega}_t = \Sigma^{-1}\Sigma_1\omega_t \quad \text{for} \quad 1 \le t \le N_1, \tag{IA.26}$$

$$\tilde{\omega}_t = \Sigma^{-1}\Sigma_2\omega_t \quad \text{for} \quad N_1 + 1 \le t \le N. \tag{IA.27}$$

Let us also define

$$D_i = \Sigma^{-1}\Sigma_i, \; i = \{1, 2\} \tag{IA.28}$$

to be a diagonal scaling matrix and note that

$$\Omega_i = A\Sigma_i\Sigma_i'A' = A\Sigma D_i D_i'\Sigma'A'. \tag{IA.29}$$

This implies that in a given subsample, $\tilde{\omega}_t$ will not have a unit variance. For example, if the conditional volatility is higher in subsample 1 than in subsample 2 ($\sigma_1^i > \sigma_2^i$), then $\tilde{\omega}_t^i = \frac{\sigma_1^i}{\sigma^i}\omega_t^i$ for $1 \leq t \leq N_1$, $\frac{\sigma_1^i}{\sigma^i} > 1$, and hence the variance of $\tilde{\omega}_t^i$ will be above unity in subsample 1 and below unity in subsample 2. This is the intuition behind results in Figure IA-3, where the shocks estimated over subsample are close to but not exactly on the 45-degree line.[1]

The above analysis indicates, that under the assumption that matrix A is constant (i.e., structural relations in the economy do not change over time), we are able to recover structural shocks up to the scaling by their time-varying volatilities. As such, the historical decompositions of yield changes and stock returns in equation (19) will correctly describe the contributions of structural shocks given that $A\Sigma J_{ss}\tilde{\omega}_t = A\Sigma_i J_{ss}\omega_t$ for shocks indexed by s and a subsample $i = \{1, 2\}$.

One implication of the setting in equation (IA.24) is that the only way the covariance of stocks and yields can move around over time is due to time-varying volatilities of structural shocks. To understand if this is plausible empirically, we analyze if the constant A assumption is consistent with the switching sign of the stock-yield covariances we observe empirically. We treat the 1983–1997 period as subsample 1 and 1998–2017 period as subsample 2. In practice, we do not observe the true value of $A\Sigma_t$, but rather we use the median-target (MT) solution over the full 1983–2017 sample as point estimate of $\tilde{A} = A\Sigma$. Let us denote the full-sample MT solution as $\widehat{\tilde{A}}$. We estimate reduced-form variance-covariances of innovations from VAR(1) residuals over the two subsamples, $\widehat{\Omega}_1, \widehat{\Omega}_2$. Then, we search for empirical analogs of the diagonal scaling matrices $\widehat{D}_1$ and $\widehat{D}_2$ defined in equation (IA.28) by minimizing $\widehat{D}_i = \underset{D_i}{\operatorname{argmin}} || \frac{\widehat{\Omega}_i - \widehat{\tilde{A}} D_i D_i' \widehat{\tilde{A}}'}{\widehat{\Omega}_i} ||$, where $\widehat{D}_i$ is a diagonal matrix and where we keep $\widehat{\tilde{A}}$ constant at the full-sample value. The norm $|| \cdot ||$ is a 2-norm of matrix (approximately the maximum singular value of a matrix),[2] and the fraction denotes element-wise division, which serves to standardize the differences across elements of $\widehat{\Omega}_i$. Note that, if we replace all the hat terms with their true value, the norm should be equal to 0.

The difference between D_1 and D_2 describes how the volatility of structural shocks varies across the two subsamples. For 1983–1997 and 1998–2017 samples, respectively, we have

$$\widehat{D}_1 = \begin{pmatrix} 0.93 & 0 & 0 & 0 \\ 0 & 1.16 & 0 & 0 \\ 0 & 0 & 0.66 & 0 \\ 0 & 0 & 0 & 1.18 \end{pmatrix}, \quad \widehat{D}_2 = \begin{pmatrix} 1.05 & 0 & 0 & 0 \\ 0 & 0.84 & 0 & 0 \\ 0 & 0 & 1.17 & 0 \\ 0 & 0 & 0 & 0.81 \end{pmatrix}$$

where the diagonal elements are ordered to correspond to $\omega^g, \omega^m, \omega^{p+}, \omega^{p-}$ shocks. We can now compare the reduced-form covariances that are consistent with a constant A assumption (at the full-sample MT solution) with unconstrained equivalents $\widehat{\Omega}_i$ in each subsample i:

$$\widehat{\Omega}_1 = \begin{pmatrix} 0.004 & 0.004 & 0.003 & -0.012 \\ 0.004 & 0.004 & 0.004 & -0.019 \\ 0.003 & 0.004 & 0.004 & -0.022 \\ -0.012 & -0.019 & -0.022 & 0.894 \end{pmatrix}, \quad \widehat{\tilde{A}}\widehat{D}_1\widehat{D}_1\widehat{\tilde{A}}' = \begin{pmatrix} 0.003 & 0.003 & 0.003 & -0.012 \\ 0.003 & 0.004 & 0.004 & -0.016 \\ 0.003 & 0.004 & 0.004 & -0.021 \\ -0.012 & -0.016 & -0.021 & 1.103 \end{pmatrix}$$

[1]We note that regressions in Figure IA-3 do not impose that A is constant in subsamples and equal to the full sample estimates.

[2]The 2-norm of an $m \times m$ matrix M is defined by $\max_{\vec{v} \neq \vec{0}} \frac{||M\vec{v}||_2}{||\vec{v}||_2}$, where $\vec{v}$ is a non-zero m-dimensional vector.

$$\widehat{\Omega}_2 = \begin{pmatrix} 0.003 & 0.003 & 0.002 & 0.020 \\ 0.003 & 0.004 & 0.003 & 0.024 \\ 0.002 & 0.003 & 0.004 & 0.023 \\ 0.020 & 0.024 & 0.023 & 1.455 \end{pmatrix}, \quad \widehat{\widetilde{A}}\widehat{D}_2\widehat{D}_2\widehat{\widetilde{A}}' = \begin{pmatrix} 0.003 & 0.003 & 0.003 & 0.020 \\ 0.003 & 0.004 & 0.003 & 0.023 \\ 0.003 & 0.003 & 0.004 & 0.023 \\ 0.020 & 0.023 & 0.023 & 1.226 \end{pmatrix}$$

Recall that both ω^{p+} and ω^{g} (ω^{m} and ω^{p-}) shocks move yields and stocks in the same (opposite) direction. We see that the time-varying volatility of structural shocks alone can generate a switching sign of the stock-yield covariances. In particular, the switch from negative to positive stock-yield covariance in the late 1990s is due to the increase in volatility of the hedging premium shocks ω^{p+} and decrease in the volatility of the common premium shocks ω^{p-}; this effect is amplified by the increased volatility of growth news ω^{g} and decline in volatility of monetary news ω^{m}.

B. 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):

$$F_{t+1} = \mu_F + \Phi_F F_t + \Sigma_F \omega_{t+1}, \tag{IA.30}$$

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

$$i_t = \delta_0 + \delta_\tau \tau_t + \delta_g g_t + m_t = \delta_0 + \delta_1' F_t, \tag{IA.31}$$

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

$$\xi_{t+1} = \ln M_{t+1} = -i_t - \frac{1}{2}\Lambda_t'\Lambda_t - \Lambda_t'\omega_{t+1}, \tag{IA.32}$$

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:

$$\begin{aligned} y_t^{(n)} &= b_n + B_n' F_t \\ p_t^{(n)} &= -n y_t^{(n)} = -n b_n - n B_n' F_t. \end{aligned} \tag{IA.33}$$

Given that equilibrium bond prices satisfy

$$\exp(p_t^{(n)}) = E_t[\exp(\xi_{t+1} + p_{t+1}^{(n-1)})], \tag{IA.34}$$

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

$$B_n = \frac{n-1}{n}(\Phi - \Lambda_1)' B_{n-1} + \frac{1}{n}\delta_1. \tag{IA.35}$$

The one-period expected log excess bond returns are:

$$E_t(rx_{t+1}^{(n)}) + \frac{1}{2}Var_t(rx_{t+1}^{(n)}) = -Cov_t(\xi_{t+1}, \frac{p_{t+1}^{(n-1)}}{p_t^{(n)}}). \tag{IA.36}$$

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

$$r_{t+1}^s = \kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t. \tag{IA.37}$$

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

$$pd_t = b_s + B_s' F_t. \tag{IA.38}$$

Using the fact that stock returns satisfy

$$\ln E_t[\exp(\xi_{t+1}^r + r_{s,t+1})] = 0, \tag{IA.39}$$

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

$$B_s' = (\delta_1' - \theta')[\kappa_1(\Phi_F - \Lambda_1) - I]^{-1}, \tag{IA.40}$$

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

$$E_t(rx_{t+1}^s) + \frac{1}{2} Var_t(rx_{t+1}^s) = -Cov_t(\xi_{t+1}^r, r_{t+1}^s). \tag{IA.41}$$

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	$B_n^i = \frac{\delta_i}{n} \frac{1-\phi_i^n}{1-\phi_i} > 0$, $i = \{\tau, g, m\}$ $B_n^{x^+} = \frac{n-1}{n} \phi_{x^+} B_{n-1}^{x^+} - \frac{n-1}{n} B_{n-1}^g \lambda_{gx^+} < 0$ $B_n^{x^-} = \frac{n-1}{n} \phi_{x^-} B_{n-1}^{x^-} - \frac{n-1}{n} B_{n-1}^m \lambda_{mx^-} > 0$
pd ratio loadings	$B_s^g = \frac{1-\delta_g}{1-\kappa_1 \phi_g} > 0$ $B_s^\tau = \frac{1-\delta_\tau}{1-\kappa_1 \phi_\tau} < 0$ $B_s^m = -\frac{1}{1-\kappa_1 \phi_m} < 0$ $B_s^{x^+} = \frac{-\kappa_1 \lambda_{gx^+} B_s^g}{1-\kappa_1 \phi_{x^+}} < 0$ $B_s^{x^-} = \frac{-\kappa_1 \lambda_{fx^-} B_s^m}{1-\kappa_1 \phi_{x^-}} < 0$
Bond expected excess returns	$\text{const.} \underbrace{-(n-1) B_{n-1}^g}_{(-)} \lambda_{gx^+} x_t^+ \underbrace{-(n-1) B_{n-1}^m}_{(-)} \lambda_{mx^-} x_t^-$
Stock expected excess returns	$\text{const.} + \kappa_1 (\underbrace{B_s^g}_{(+)} \lambda_{gx^+} x_t^+ + \underbrace{B_s^m}_{(-)} \lambda_{mx^-} x_t^-)$

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 $B_n^\tau = \frac{n-1}{n} \phi_\tau B_{n-1}^\tau + \frac{n-1}{n} \phi_{g\tau} B_{n-1}^g + \frac{\delta_\tau}{n}$ and $B_s^\tau = \frac{1+\kappa_1 \phi_{g\tau} B_s^g - \delta_\tau}{1-\kappa_1 \phi_\tau}$ 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 14 in the paper). When $\Phi_{F(2,3)} = \phi_{gm} < 0$, expected monetary policy negatively affect expected growth. Then, $B_n^m = \frac{n-1}{n} \phi_m B_{n-1}^m + \frac{n-1}{n} \phi_{gm} B_{n-1}^g + \frac{1}{n}$ and $B_s^m = \frac{\kappa_1 \phi_{gm} B_s^g - 1}{1-\kappa_1 \phi_m} < 0$ with expressions for other loadings unchanged. When the negative feedback of monetary policy on expected growth is not too strong, we have $B_n^m > 0$ across maturities (in line with the empirical literature) and thus, the sign of the loadings remain as in the diagonal Φ_F case.

C. 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:

$$y_t^{(n)} = \frac{1}{n} E_t \left(\sum_{i=0}^{n-1} y_{t+i}^{(1)} \right). \tag{IA.42}$$

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):

$$X_t = \Phi X_{t-1} + \epsilon_t. \tag{IA.43}$$

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

$$y_t^{(n),EH} = \text{const.} + \frac{1}{n} \gamma' (I - \Phi)^{-1} (I - \Phi^n) X_t. \tag{IA.44}$$

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

$$Z_t = \Lambda Z_{t-1} + C^{-1} \epsilon_t. \tag{IA.45}$$

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

$$y_t^{(n)} - \text{const.} = \gamma' (\frac{1}{n} (I - \Phi)^{-1} (I - \Phi^n)) X_t = \gamma' (\frac{1}{n} \sum_{i}^{n-1} \Phi^i) X_t = \tag{IA.46}$$

$$\gamma' (\frac{1}{n} \sum_{i}^{n-1} C \Lambda^i C^{-1}) C Z_t = \gamma' C (\frac{1}{n} \sum_{i}^{n-1} \Lambda^i) Z_t = \gamma' C \tilde{\Lambda} Z_t \tag{IA.47}$$

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.

D. Identification restrictions

As stated in Section III.B, we impose three types of restrictions on entries of instantaneous response matrix $\tilde{A}$:

$$\tilde{A} = A\Sigma_F = \begin{pmatrix} A_g^{(2)} & A_m^{(2)} & A_{p+}^{(2)} & A_{p-}^{(2)} \\ A_g^{(5)} & A_m^{(5)} & A_{p+}^{(5)} & A_{p-}^{(5)} \\ A_g^{(10)} & A_m^{(10)} & A_{p+}^{(10)} & A_{p-}^{(10)} \\ A_g^{s} & A_m^{s} & A_{p+}^{s} & A_{p-}^{s} \end{pmatrix} \begin{pmatrix} \sigma_g & 0 & 0 & 0 \\ 0 & \sigma_m & 0 & 0 \\ 0 & 0 & \sigma_{p+} & 0 \\ 0 & 0 & 0 & \sigma_{p-} \end{pmatrix}. \tag{IA.48}$$

We cannot identify A and Σ_F separately. However, given that σ's are all strictly positive, Most of our restrictions are equivalent to imposing them directly on entries of the A matrix.

Sign restrictions:

We impose 16 sign restrictions on each of the 16 entries of $\tilde{A}$.

$$\begin{pmatrix} A_g^{(2)} > 0 & A_m^{(2)} > 0 & A_{p+}^{(2)} \leq 0 & A_{p-}^{(2)} > 0 \\ A_g^{(5)} > 0 & A_m^{(5)} > 0 & A_{p+}^{(5)} \leq 0 & A_{p-}^{(5)} > 0 \\ A_g^{(10)} > 0 & A_m^{(10)} > 0 & A_{p+}^{(10)} \leq 0 & A_{p-}^{(10)} > 0 \\ A_g^{s} > 0 & A_m^{s} \leq 0 & A_{p+}^{s} \leq 0 & A_{p-}^{s} \leq 0 \end{pmatrix} \tag{IA.49}$$

Between-asset restrictions:

Growth shock: $|A_g^{(2)}| > |A_g^{(10)}|$ and $|A_g^{(5)}| > |A_g^{(10)}|$,
Monetary policy shock: $|A_m^{(2)}| > |A_m^{(5)}| > |A_m^{(10)}|$,
Hedging risk premium shock: $|A_{p+}^{(2)}| < |A_{p+}^{(5)}| < |A_{p+}^{(10)}|$,
Common risk premium shock: $|A_{p-}^{(2)}| < |A_{p-}^{(5)}| < |A_{p-}^{(10)}|$.

Within-asset restrictions:

Two-year yield: $(A_m^{(2)}\sigma_m)^2 + (A_g^{(2)}\sigma_g)^2 > (A_{p+}^{(2)}\sigma_{p+})^2 + (A_{p-}^{(2)}\sigma_{p-})^2$
Ten-year yield: $(A_m^{(10)}\sigma_m)^2 + (A_g^{(10)}\sigma_g)^2 < (A_{p+}^{(10)}\sigma_{p+})^2 + (A_{p-}^{(10)}\sigma_{p-})^2$

E. Bootstrap

Inference in set-identified structural VAR models is complex, especially from a frequentist perspective. As in our setting, there are two sources of uncertainty stemming from the estimation of the reduced-form VAR parameters and from the model multiplicity induced by the set-identified structural parameters. Faust, Swanson, and Wright (2004) (FSW) use bootstrap-based inference and Bonferroni inequality to combine two uncertainties into one confidence interval for functions of parameters (e.g., impulse response functions and variance decompositions). Granziera, Moon, and Schorfheide (2018) (GMS) provide a more general inference methodology that shares the intuition with FSW. The idea is to first generate a confidence set for structural parameters, which are derived from the estimates of the reduced-form parameters and of their asymptotic covariance matrix. Then, conditional on any single draw of structural parameters from this confidence set, one obtains bootstrap confidence set for point-identified reduced-form parameters and thus point-identified functions of interest. Finally, Bonferroni inequality is used to combine these two sets into one confidence interval. However, these methodologies only apply to inference on functions of parameters but not functions of both parameters and data. We are interested in assessing the uncertainty about the time series of structural shocks, impulse response function based on local projections (Jordà, 2005), and historical decomposition of observables.

Inspired by the literature above, we adopt a bootstrap-based approch that can jointly measure the two uncertainties and applies to functions of both parameters and data. We start by bootstraping the reduced-form VAR model to asses the uncertainty stemming from the estimation of reduced-form parameters. As in a standard residual-based bootstrap, using the maximum-likelihood estimates of the VAR, we obtain the reduced-form shock series (residuals) and draw randomly with replacement to form an artificial shock series with the same length as the original one. We then construct an artificial yield changes and stock returns by iterating the estimated VAR model date by date with the artificial shocks and initial values equal to the data. In the next step, we apply our identification procedure on the artificial data to generate a set of valid structural models[3] $\{\boldsymbol{\Phi}(L), \tilde{\boldsymbol{A}}\} = \{\Phi_i(L), \tilde{A}_{i,j}, j = 1, 2, ..., N_{valid}\}$ for the bootstrap trial i, where $N_{valid} = 1000$ is the number of models satisfying identification restrictions retained within each trial. By repeating the bootstrap process $N_{bs} = 1000$ times, we obtain a pool of $N_{bs} \times N_{valid}$ models $\{\Phi_i(L), \tilde{A}_{i,j}, j = 1, 2, ..., N_{valid}\}_{i=1,2,...,N_{bs}}$. The set of all structural parameters A within this pool is analogous to the set of structural parameters derived in FSW and GMS. The difference is that they draw from the analytical asymptotic distribution of reduced-form parameters, while we bootstrap the residuals.

With the $N_{bs} \times N_{valid}$ pool of models, using parameters $\{\boldsymbol{\Phi}(L), \tilde{\boldsymbol{A}}\}$, we can compute variance ratios and assess their uncertainty. However, since models are based on bootstrapped artificial data, we cannot obtain meaningful shock series and historical decompositions of asset returns over time. Therefore, for inference on objects relying on both parameters and data (e.g., structural shocks, historical decompositions, etc.), we adopt a modified bootstrap procedure. Instead of set-identifying structural parameters based on artificial reduced-form shocks, we take the VAR parameters $\Phi_i(L)$ from the bootstrap back to the original data series and reconstruct the reduced-form shocks. We then apply the identification procedure on the new reduced-form shocks and obtain $\{\tilde{A}_{i,j}\}_{j=1,2,...,N_{valid}}$. We can now back out the time series of cumulative shocks as $\{W_t^{i,j}\}_{t=1,2,..,T}$. This process results in $N_{bs} \times N_{valid}$ structural shocks series, whose distribution represents the sum of two types of uncertainty.

[3] A structural model is defined as $\{\Phi, A\}$, a pair of reduced-form parameters and structural parameters.

To illustrate estimation uncertainty alone, Figure IA-1 presents the percentiles of the median cumulative shocks ($W_t^{i,med} = \text{median}(W_t^{i,j})$) across i at each t. That is, within each bootstrap trial i, we take the median of shocks over all N_{valid} models;[4] we then construct confidence intervals as percentiles over the N_{bs} median cumulative shock series at each t. The error bands only represent the estimation uncertainty because the median of shocks in each bootstrap trial is a point estimate and therefore does not reflect model uncertainty stemming from the set identification. The narrow error bands shown in Figure IA-1 reflect the fact that the estimation uncertainty stems primarily from the estimation of the covariance matrix of the reduced-form shocks. Because yield changes and stock returns mean-revert quickly, the estimation precision of the feedback parameters in the VAR does not significantly affect the estimation of the reduced-form shocks.

[4] As argued above, the total uncertainty is represented by the distribution of all $N_{bs} \times N_{valid}$ structural shocks series. We can view this distribution as a joint distribution $f(\Phi, A)$ of both reduced-form and structural parameters, where $f(\cdot,\cdot)$ represents the pdf. Then, to eliminate model uncertainty, we should integrate over structural parameters. We use the median of shocks rather than shocks from the MT solution because taking median of shocks over structural parameters better represents this integral operation (MT solution is a non-linear operator over the distribution).

F. Additional tables and figures

Study	Effect on stocks	Effect on yields	Main sample period
Monetary shocks (tightening news)			
Poole, Rasche, and Thornton (2002)		+, ↘	pre-1994, 1994-2002
Rigobon and Sack (2004)	−	+, ↘	1994:1-2001:11
Gürkaynak, Sack, and Swanson (2005b)		+, ↘	1990:1-2002:12
Bernanke and Kuttner (2005)	−	+, ↘	1989:6-2002:12
Gürkaynak, Sack, and Swanson (2005a)	−	+, ↘	1990:1-2004:12
Campbell, Evans, Fisher, and Justiniano (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.

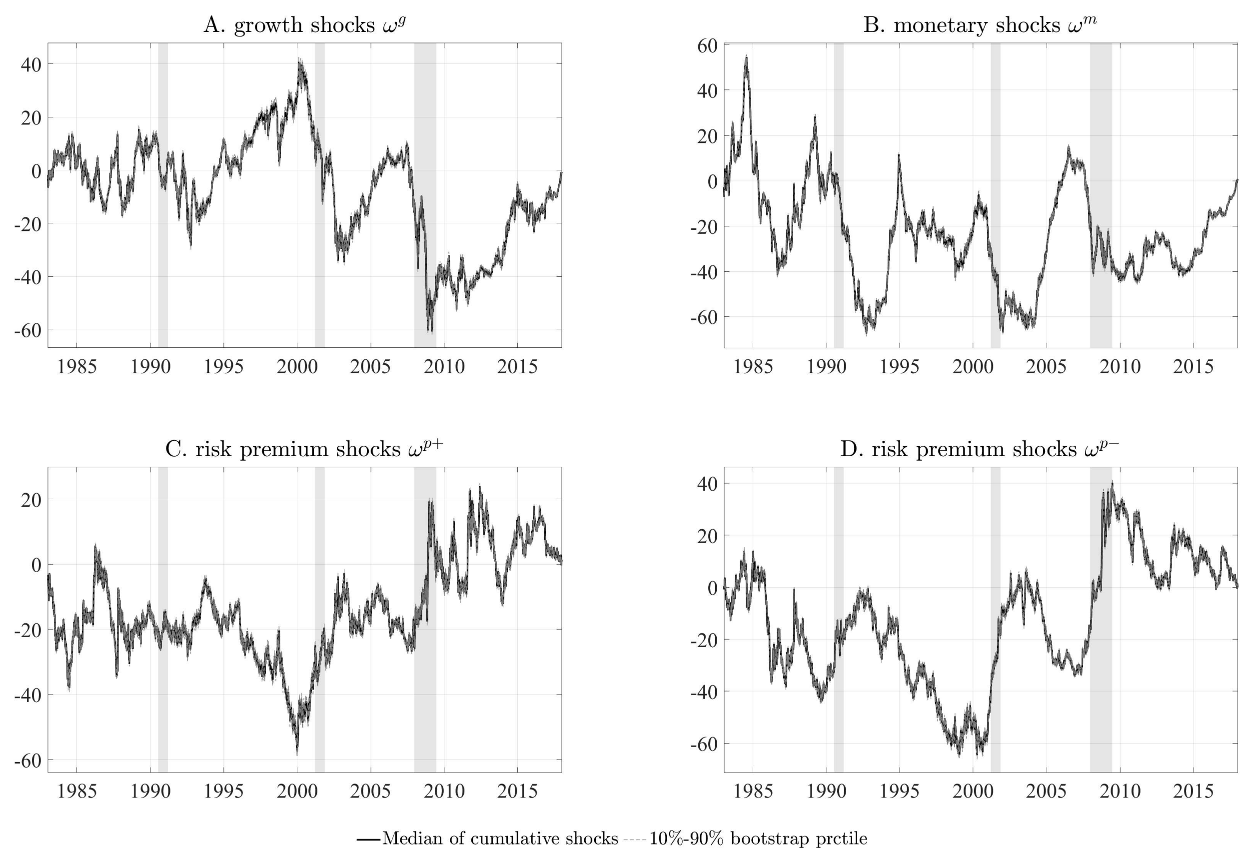

Figure IA-1. Estimation uncertainty. The figure presents 10-90% bootstrap confidence interval around the median of cumulative shocks. The bootstrap procedure is explained in Appendix E.

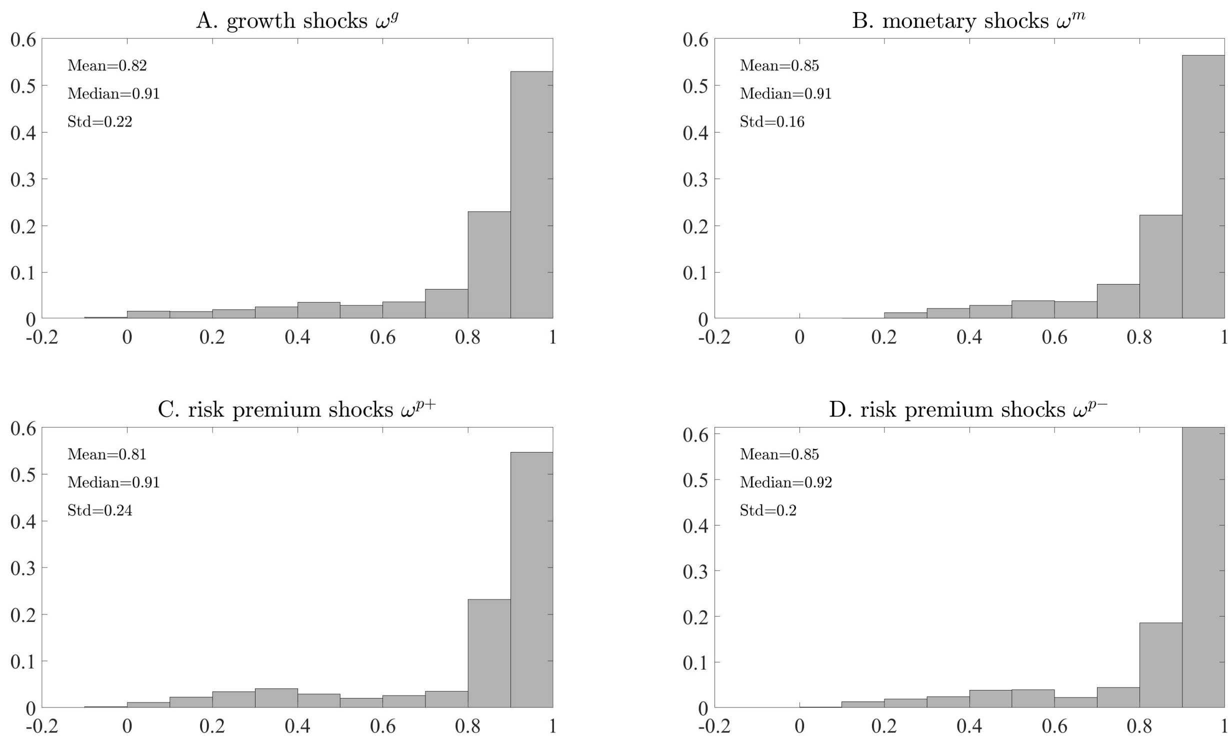

Figure IA-2. Correlation of shocks from different models. The figure presents the distribution of correlation coefficients across all retained solutions. For each structural shock j associated with solution i we calculate its correlation with shock j associated with the MT solution, and plot the histogram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

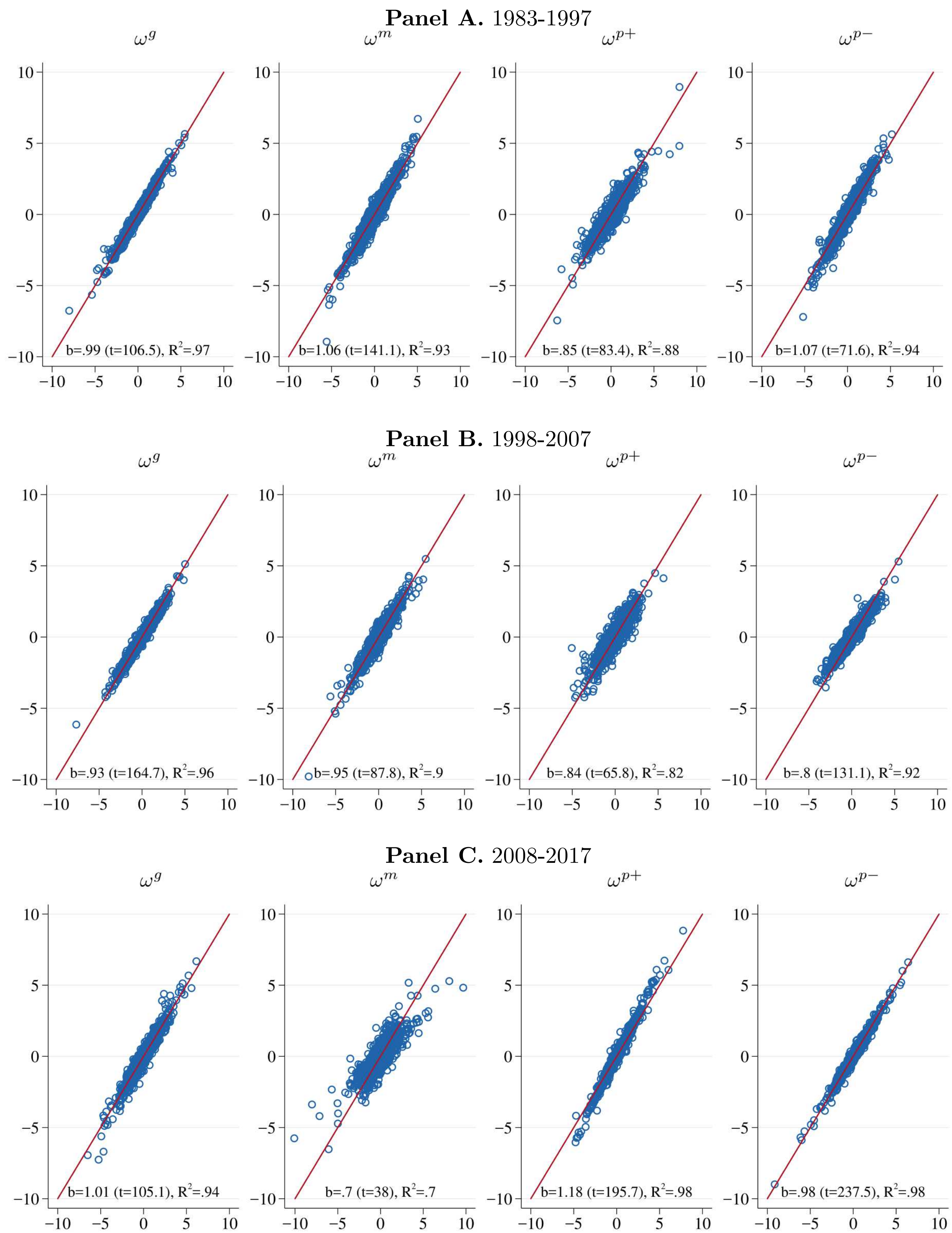

Figure IA-3. Shocks estimated over subsamples. The figure presents scatter plots of shocks estimated over the full sample, 1983–2017 (on the y-axis) against shocks estimated over subsamples (on the x-axis). Each plot contains a 45-degree line, and reports the slope coefficient, robust t-statistic and R^2 from a regression of full-sample shocks on the subsample shocks. The subsample shocks are guaranteed to have a unit standard deviation.

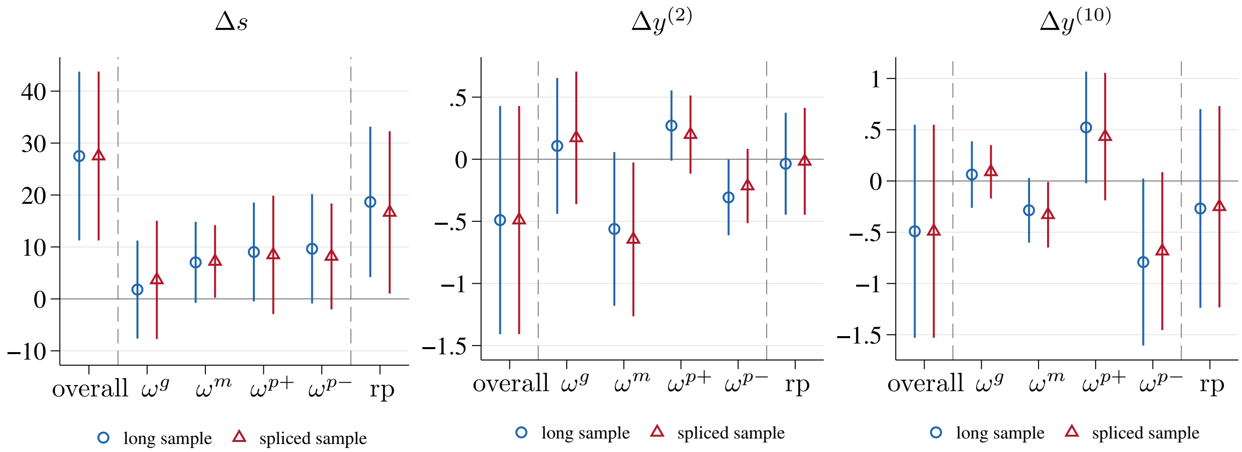

Figure IA-4. Stock returns and yield changes on FOMC days. The figure provides a robustness check to Figure 2, by comparing coefficients of regression (20) obtained using two sets of shocks and historical decompositions (HD) of asset returns. For the "long sample" results, shocks and HDs are estimated over the entire 1983–2017 period; for the "spliced sample" results, they are estimated separately over the 1983–1997 and 1998–2017 periods and combined. In both cases, the regressions in equation (20) are estimated over the 1994–2017 sample. The spikes indicate 95% confidence intervals based on standard errors robust to heteroscedasticity.

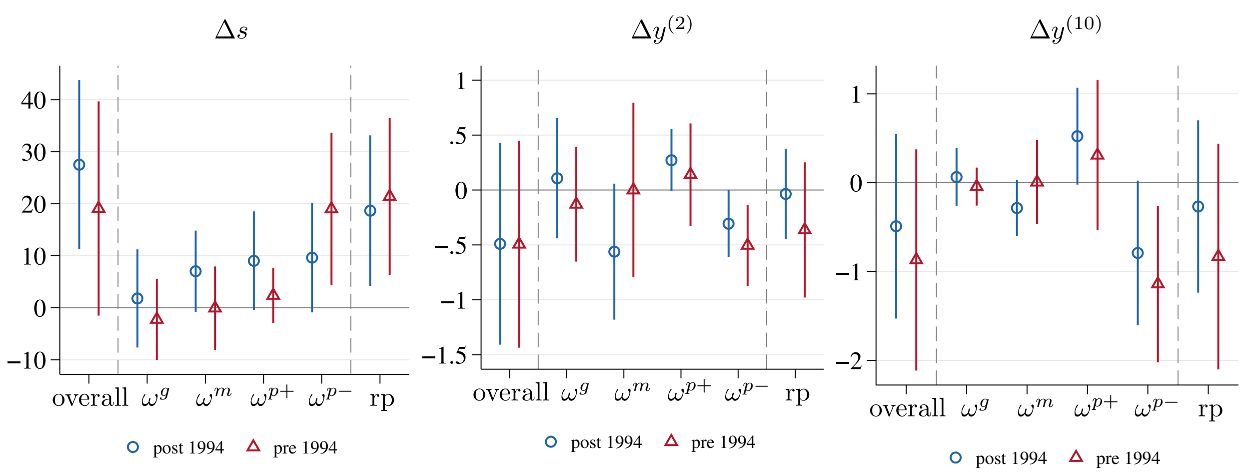

Figure IA-5. Stock returns and yield changes on FOMC days: Pre- and post-1994 comparison. The figure compares the results from regression (20) over the pre- and post-1994 samples. The post-1994 results are the same as reported in Figure 2. The pre-1994 results are based on the shocks estimated using data through the end of 1997 (when the stock-bond covariance switched sign), with result being quantitatively and qualitatively similar if we use shocks estimated over the full 1983–2017 sample. The spikes indicate 95% confidence intervals based on standard errors robust to heteroscedasticity.

	(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)
$[10\%, 90\%]$	–	[-0.92, 13.2]	[0.34, 16.4]	[0.21, 17.4]	[1.59, 18.9]	[3.52, 27.3]
$[5\%, 95\%]$	–	[-1.10, 17.2]	[0.11, 19.9]	[-0.23, 20.3]	[0.77, 21.8]	[1.21, 27.9]
		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)
$[10\%, 90\%]$	–	[-0.28, 0.48]	[-0.86, -0.14]	[-0.046, 0.43]	[-0.61, -0.0089]	[-0.47, 0.29]
$[5\%, 95\%]$	–	[-0.21, 0.42]	[-0.81, -0.21]	[-0.0067, 0.37]	[-0.53, -0.028]	[-0.36, 0.21]
		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)
$[10\%, 90\%]$	–	[-0.11, 0.26]	[-0.54, -0.030]	[-0.027, 0.58]	[-0.92, -0.33]	[-0.55, -0.0093]
$[5\%, 95\%]$	–	[-0.20, 0.32]	[-0.60, -0.012]	[-0.13, 0.60]	[-0.98, -0.22]	[-0.64, 0.057]

Table IA-2. FOMC day dummy regressions (all retained solutions). The table reports regressions of log stock returns and yield changes and their historical decompositions on the FOMC day dummy for scheduled FOMC meetings (equation (20)). All coefficients are in basis points. Regression intercepts are not reported. The point estimates in rows "FOMC day dummy" are for the MT solution (robust t-statistics in parentheses). Rows $[10\%, 90\%]$ and $[5\%, 95\%]$ report the 10th/90th and 5th/95th percentiles of the distribution of slope coefficients in regression (20) across all 1000 retained model solutions. In column (1), the dependent variable is the overall return or yield change, hence no intervals are reported. 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, coefficients on FOMC day dummy 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 for all models are estimated over the 1983–2017 sample.

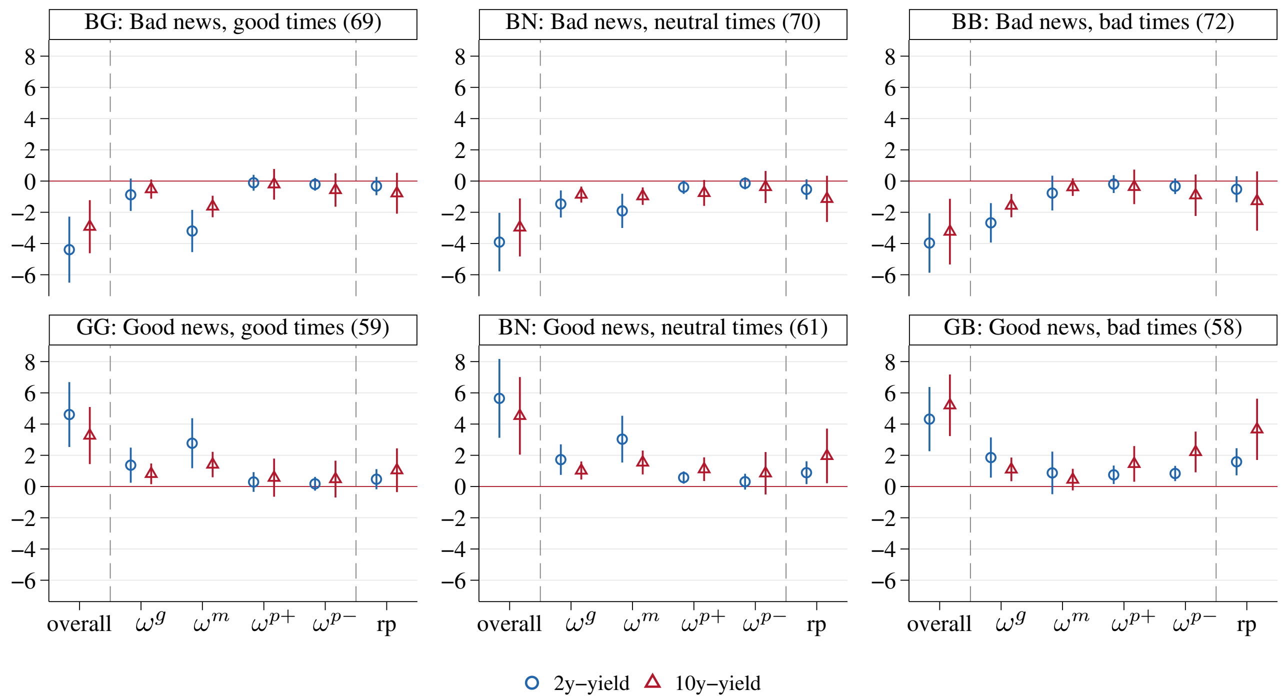

Figure IA-6. Yield changes on days of employment report announcement. The figure reports average two- and ten-year yield changes and their decompositions into contributions of structural shock on NFP announcement days, conditional on the type of news and the state of the economy. All numbers are in basis points. Good/Bad NFP news corresponds to the positive/negative NFP surprises (actual less expected NFP). The state of the economy (Good/Neutral/Bad times) is measured using the terciles of the Gap variable, Gap = −(Current unemployment − Natural rate of unemployment), with Gap in top tercile indicating good times. The estimates are obtained as β_k coefficients from regression (21), $k = \{\text{BG, BN, BB, GG, GN, GB}\}$. Each subplot combines estimates of β_k for a given k from six regressions, using a different dependent variable each. The sample period is 1985:2–2017, with 389 NFP announcements for which we have both survey and actual numbers, excluding announcements that fall on a holiday. NFP surprises before 1997 are from Money Market Services, and from 1997 onward from Bloomberg. In parentheses, we report the number of NFP announcements falling into bin k. The spikes indicate 95% confidence intervals based on robust standard errors.

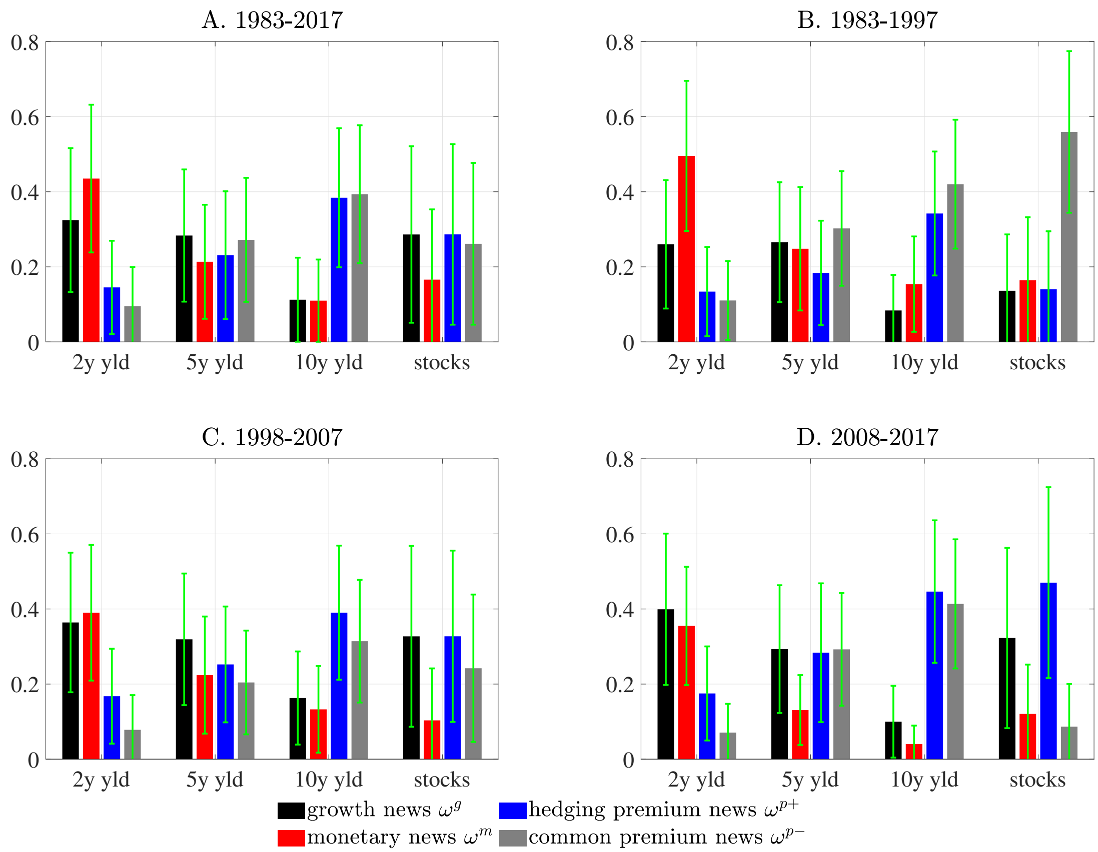

Figure IA-7. Variance decompositions. The figure presents variance decompositions of daily yield changes and stock market returns. The bars show the average fraction of variance explained by each shock, with average of that fraction taken across retained solutions. The error bars display one standard 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 4, which presents variance decompositions for the MT solution.

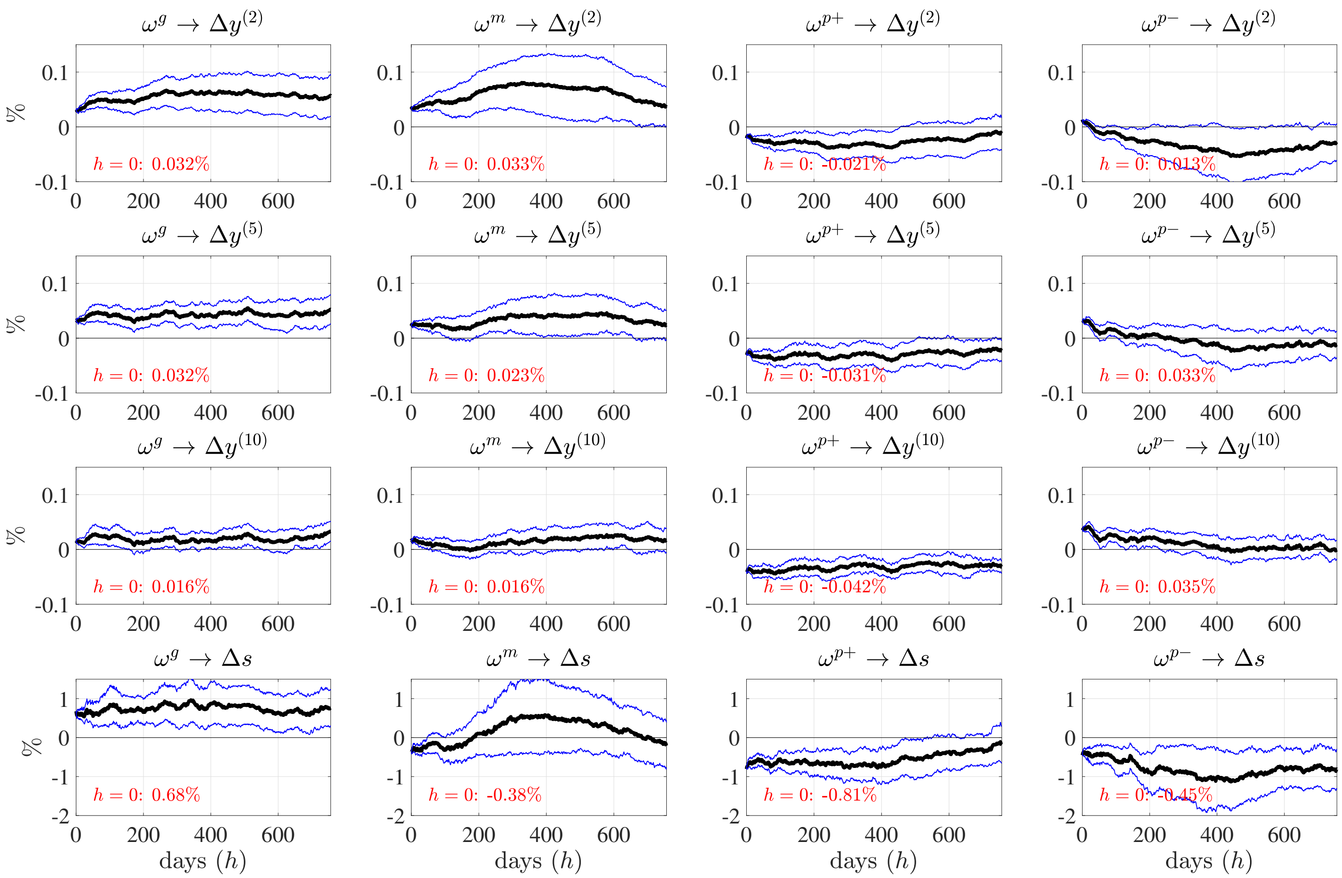

Figure IA-8. Impulse-response functions (1998–2017 sample). The figure presents impulse-response functions of yield changes and log stock returns to structural shocks. The shocks and the impulse responses are estimated on the 1998–2017 sample for comparison with Figure 5 in the paper, which is based on the 1983–2017 sample. Shocks are measured in units of standard deviation. Yield changes and stock returns are in percent. The thick line traces out the coefficients $\beta_h^{j,i}$ from regression (23). A coefficient of 0.1 implies an asset response of 0.1% 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 $h = 0$).

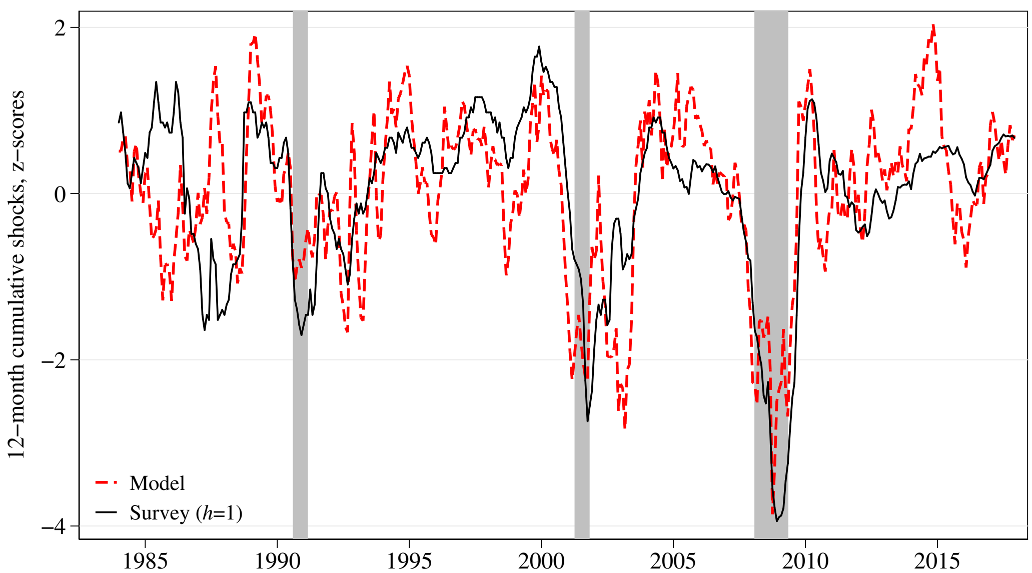

Figure IA-9. Time series of growth shocks and survey forecast updates for real GDP growth. The figure superimposes growth shocks with the forecast updates of real GDP growth expectations from the BCEI survey. The shocks and survey updates are cumulative over a 12-month period. Survey updates are for the next quarter ($h = 1$). 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-3. 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 V and VI.

A. Monthly frequency ($N = 120$)				
Variables	ω^g	ω^m	ω^{p+}	ω^{p-}
ω^g	1.00			
ω^m	0.13	1.00		
	(0.01)			
ω^{p+}	0.03	-0.14	1.00	
	(0.57)	(0.00)		
ω^{p-}	-0.03	-0.07	-0.07	1.00
	(0.49)	(0.14)	(0.15)	

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

Table IA-4. 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. Correlation p-values are in parentheses.

	(1) $0 \rightarrow 1m$	(2) $1 \rightarrow 2m$	(3) $2 \rightarrow 3m$	(4) $4 \rightarrow 6m$	(5) $7 \rightarrow 12m$	(6) $0 \rightarrow 12m$
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-5. 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 VI Panel A.