

Economic Shocks in Stock, Corporate Bond, and Treasury Bond Markets

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Abstract

We analyze the economic sources underlying time-varying dynamics and comovements of Treasury yields, corporate bond yields, and stock returns. Employing a structural vector autoregression (SVAR) model identified via sign, zero, and within-asset restrictions, we isolate five distinct economic shocks: growth, monetary, and three types of risk premium shocks—common, hedging, and default. We find investors' responses to news from the Federal Reserve and macroeconomic announcements are strongly state-dependent, significantly more pronounced during economic downturns, and predominantly driven by risk premium shocks rather than changes in monetary or growth expectations. Structural decompositions further demonstrate that risk premium shocks, especially default and hedging premia, largely explain asset price comovements across major financial crises.

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1 Introduction

What are the economic shocks driving the aggregate stock market, the corporate bond market, and the Treasury bond market, and how do these shocks account for their comovements? While existing studies often focus on the relationship between the stock market and Treasury market (e.g., [Campbell and Ammer, 1993](#); [Connolly et al., 2005](#); [Baele et al., 2010](#); [Bansal et al., 2010](#); [Cieslak and Pang, 2021](#); [Ermolov, 2022](#), and [Duffee, 2023a](#))¹, they usually overlook the role of corporate bonds. However, corporate bonds are a key part of the financial system, reflecting factors like credit risk, interest rates, and macroeconomic conditions (e.g., [Philippon, 2009](#); [Gilchrist and Zakrajšek, 2012](#)).² Omitting corporate bonds can result in incomplete and potentially biased interpretations of economic interactions and asset pricing dynamics, as well as the comovements among assets. This paper aims to bridge this gap by incorporating corporate bonds into the analytical framework, providing a more comprehensive understanding of how economic shocks shape asset pricing dynamics and the comovements across major financial markets, while reducing the risk of biased interpretations that result from excluding them.

[Cieslak and Pang \(2021\)](#) recently propose a framework to identify economic shocks, including monetary, growth, and risk premium shocks (specifically, common and hedging premium shocks), from stock returns and Treasury yield changes. They use this identification to study investor responses to Federal Reserve communications and key macroeconomic announcements at a daily frequency. Building on their framework, we extend the analysis by incorporating corporate bonds alongside stocks and Treasuries, using two-year and ten-year Treasury yields, investment-grade and high-yield corporate bond yields, and stock returns. This broader set of instruments captures three major markets, the term structure, and

¹[Baele et al. \(2020\)](#) find that on flight-to-safety (FTS) days, equity and high-yield corporate bond funds experience significant outflows, while government-only money market funds receive significant inflows.

²Corporate bond markets have grown significantly since the 2008 financial crisis. Globally, the total outstanding amount of corporate bond debt has grown in real terms from USD 21.0 trillion in 2008 to USD 33.6 trillion in 2023 ([OECD, 2024](#)).

differences in credit quality, providing a more comprehensive perspective on how economic shocks drive asset pricing dynamics and cross-asset comovements. We consider three sets of identification restrictions: sign restrictions, zero restrictions, and inequality restrictions across the yield curve and credit rating. Our approach employs a theoretically motivated and intuitive identification strategy to isolate five distinct, mutually orthogonal economic shocks: a growth shock, a monetary shock, and three risk premium shocks, including common, hedging, and default risk premium shocks. Our identification strategy offers a natural way to transform reduced-form innovations in asset prices, which are often interpreted as cash flow news, risk-free rate news, and risk premium news in finance (e.g., [Campbell, 1991](#) and [Campbell and Ammer, 1993](#)), into orthogonal structural shocks in economics (e.g., [Sims, 1980](#)) corresponding to growth shocks, monetary policy shocks, and risk premium shocks. This approach provides economically meaningful interpretations of asset pricing dynamics, their comovements, and the unique characteristics of each shock without relying on the parametric assumptions of a fully specified asset pricing model.

We apply our approach to examine how asset pricing dynamics and comovements respond to economic shocks across different conditions, including Federal Open Market Committee (FOMC) announcements, non-farm payroll (NFP) announcements, and broader macroeconomic environments, allowing us to assess how markets adjust to changing fundamentals and how risk premiums and investor perceptions evolve over time (e.g., [Savor and Wilson, 2013](#); [Lucca and Moench, 2015](#); [Ai and Bansal, 2018](#); [Cieslak and Pang, 2021](#)). Our study enhances the understanding of the fundamental drivers of asset pricing and provides valuable insights for policymakers, investors, and researchers on market stability, efficiency, and risk pricing across diverse economic conditions.

We find that asset price responses to scheduled FOMC announcements are overwhelmingly state-dependent. When the economy is strong, FOMC communications exert little impact on Treasury yields, corporate bond yields, or stock returns. In contrast, during recessions or periods of weak economic activity, FOMC announcements significantly

influence almost all asset classes. Notably, the dominant transmission mechanism is not through monetary shocks or revised growth expectations, but through reductions in risk premia—especially common and default risk premium shocks. These results suggest that the Federal Reserve plays a critical stabilizing role in downturns by reshaping investor perceptions of macro-financial risks, consistent with the literature of state-dependent monetary policy transmission (e.g., [Bernstein, 2021](#); [Eichenbaum et al., 2022](#)).

We examine asset price reactions to NFP announcements, finding that investor responses depend not only on the sign of the news but also on the prevailing macroeconomic environment. For example, bad news during good times leads to equity rallies and lower risk premia, consistent with “bad news is good news” dynamics (e.g., [Lucca and Moench, 2015](#) and [Cieslak and Pang, 2021](#)). Our shock decomposition, however, reveals that the equity rally coincides with significant negative hedging premium shocks rather than pure monetary shocks, indicating that diminished flight-to-safety motives—rather than direct policy easing—explain the market’s response. Conversely, bad news in bad times results in broad-based declines across equities and credit. The structural decomposition shows that these asymmetric responses are largely explained by growth and hedging premium shocks, reflecting deteriorating growth expectations and a flight to safety. These findings underscore the importance of conditioning on the macroeconomic state when evaluating market reactions to data releases (e.g., [Boyd et al., 2005](#); [Elenev et al., 2024](#)).

We examine the structural origins of comovements across equity, Treasury, and corporate bond markets. By decomposing the correlation structure over time and across crisis episodes, we find that correlations among Treasury yields, corporate bond yields, and equity returns are highly shock-dependent and episodic. The patterns shift markedly between the Global Financial Crisis (GFC) and the COVID-19 recessions. Growth shocks played a more prominent role during the Global Financial Crisis, whereas risk premium shocks—particularly hedging and default risk components—were more influential during the COVID-19 pandemic. For instance, the Treasury-equity correlation was strongly negative

during both crises, driven by growth shocks in 2008–2009 and by hedging demand in 2020. Similarly, the high correlation between high-yield bonds and stocks during the COVID-19 pandemic was primarily due to a surge in default risk. These results highlight how structural shocks can generate heterogeneous comovement patterns depending on the economic context (e.g., [Gabaix, 2012](#); [Gilchrist and Zakrajšek, 2013](#); [Zhang et al., 2020](#)).

This study contributes to the literature in several important ways. First, we extend the framework of [Cieslak and Pang \(2021\)](#) by incorporating corporate bond yields across various ratings and explicitly modeling the default risk premium shock. In addition, we adopt a combined identification strategy that leverages sign restrictions, zero restrictions, and within-asset restrictions. This extended framework allows for a comprehensive analysis of the dynamics of the Treasury yield curve, credit yield spreads, and stock returns, as well as their comovements. Second, we provide novel evidence on asset pricing dynamics and comovements across major financial markets, as well as on the underlying economic shocks that drive them under varying conditions, echoing and extending findings in [Bekaert et al. \(2013\)](#), [He and Krishnamurthy \(2013\)](#), and [Cieslak and Pang \(2021\)](#). Third, our study is related to the literature of state-dependent macro news and monetary policy transmission (e.g., [Boyd et al., 2005](#), [Cieslak and Pang, 2021](#), and [Elenev et al., 2024](#)). Taking into account economic news events (e.g., FOMC announcements and NFP releases) across different economic episodes, we highlight that the transmission of macroeconomic shocks is strongly state-dependent and nonlinear. Collectively, our findings help clarify how macroeconomic news and monetary policy flows through financial markets and underlying shocks shape asset pricing dynamics across economic states.

This paper proceeds as follows. Section 2 develops the conceptual framework and identifications. Section 3 presents the empirical approach. Section 4 analyzes responses of asset prices. Section 5 validates shocks, while Section 6 concludes.

2 Conceptual Framework

In this section, we present a structural vector autoregression approach (SVAR) to asset pricing models and discuss the identification of economic shocks affecting asset prices. Our methodology closely follows the framework established by [Cieslak and Pang \(2021\)](#). However, we extend their approach by incorporating corporate bond yields, a novel default risk premium shock, and enhanced identification restrictions.

2.1 A structural vector autoregression approach (SVAR) to asset pricing models

To model the joint dynamics of the stock, Treasury bond, and corporate bond markets, we incorporate a diverse set of financial instruments. Specifically, we use two Treasury yields to capture the behavior of bonds across different maturities, ensuring we account for variations in the yield curve. Similar to [Cieslak and Pang \(2021\)](#), we include the log price-dividend ratio as a proxy for equity valuation. Additionally, we include two corporate bond yields with different quality ratings, investment-grade and high-yield. Including corporate bond yields enables us to analyze credit spread dynamics of bonds with various credit qualities and explore the comovements between the Treasury and corporate bond markets, as well as between the corporate bond and stock markets. We stack the following variables into a vector, Y_t ,

$$Y_t = [y_{2,t}, y_{10,t}, y_{IG,t}, y_{HY,t}, y_{S,t}]$$

where y_2 and y_{10} denote the continuously compounded yields of the two-year and ten-year Treasury notes, respectively, y_{IG} and y_{HY} denote the continuously compounded yields of the investment-grade and high-yield corporate bonds, respectively, and y_S denotes the logarithm of the price-dividend ratio. Let F_t be a vector of state variables. We assume that the vector

of asset prices, Y_t , is an affine function of the vector of state variables, F_t . That is:

$$Y_t = C_0 + CF_t \quad (1)$$

where C_0 and C are parameters characterizing investors' preferences and the dynamics of the economy. Consider Y_t follows a VAR process,

$$Y_t = \mu_Y + A(L)Y_{t-1} + u_t \quad (2)$$

where $A(L) = \sum_{k=1}^p A_k L^{k-1}$, the polynomial in the lag operator, u_t is a vector of innovations to asset yields with a variance-covariance matrix Σ_u . Substituting 1 into 2 and supposing C is invertible, one obtains:

$$F_t = \mu_F + B(L)F_{t-1} + v_t \quad (3)$$

where $\mu_F = C^{-1}(\mu_Y - (I - A(L))C_0)$, $B_k = C^{-1}A_k C$, and $v_t = C^{-1}u_t$, is a mutually uncorrelated vector of shocks of the state variables. To normalize v_t , let $v_t = \Sigma_F \eta_t$ where Σ_F is a diagonal matrix and η_t is a vector of normalized structural shocks with unit variance. Then the innovations to asset prices can be expressed as a function of the orthogonal shocks of the state variables,

$$u_t = \hat{C}\eta_t, \quad \text{where} \quad \hat{C} = C\Sigma_F \quad (4)$$

In equation (4), u_t is observable and can be obtained from the residuals in the reduced-form VAR in equation (2). Conversely, η_t represents the unobservable and orthogonal structural shocks, which constitute the sources of exogenous disturbances in macro-finance or asset pricing models, and are responsible for driving fluctuations in asset prices. The matrix $\hat{C}$ encapsulates the equilibrium relationships between structural shocks and asset yield innovations. For any set of structural equations, identifying the structural shocks requires imposing restrictions that reduce the number of free parameters to align with the number recoverable from the reduced-form representation. Therefore, it is necessary to

impose restrictions on the matrix $\hat{C}$ to summarize the responses of asset yields to structural shocks.

2.2 Identifying economic shocks from Treasury yields, corporate yields, and stock returns

Sign restrictions allow for the identification of structural shocks in asset prices by transforming reduced-form innovations without needing a fully specified asset pricing model.³ This method provides a range of possible identifications for the matrix $\hat{C}$, offering flexibility and robustness based on weaker assumptions. However, zero restrictions can further refine this process by imposing specific quantitative constraints, such as restricting certain variables from responding contemporaneously to specific shocks. This combination significantly narrows the set of admissible impulse response functions, resulting in a more precise identification of structural shocks. By leveraging both sign and zero restrictions, SVAR models become more robust and economically meaningful, as demonstrated in studies by [Arias et al. \(2018\)](#) and [Canova and De Nicro \(2002\)](#).

Asset pricing theory suggests that stock prices are driven by three key factors: the risk-free interest rate, cash flow (growth) expectations, and the equity risk premium. Accordingly, we consider five structural shocks aligned with these fundamental drivers, denoted as $\eta_t = (\eta_t^g, \eta_t^m, \eta_t^c, \eta_t^h, \eta_t^d)$. Specifically, the first four components represent shocks to investors' growth expectations, shocks to the monetary policy path, common premium shock, and hedging premium shock, respectively, consistent with [Cieslak and Pang \(2021\)](#).

We introduce a new structural shock, default premium shock (η^d), which explicitly captures credit risk, a fundamental determinant of corporate bond spreads and equity returns. This shock reflects the rising importance of distress risk as a common pricing factor across credit and equity markets, particularly during periods of elevated financial stress. The inclusion of this shock is motivated by both theoretical considerations and empirical

³For a comprehensive review of sign restrictions, refer to [Kilian and Lütkepohl \(2017\)](#).

episodes (e.g., 2008 GFC, COVID-19 shock, Eurozone crisis), suggesting that time-varying credit risk premia play a crucial role in driving asset prices, particularly during periods of financial distress or heightened uncertainty (Merton, 1974; Giesecke et al., 2011; Friewald et al., 2014; Anginer and Yıldızhan, 2018; Berndt et al., 2018).

We impose three types of restrictions: sign restrictions, zero restrictions, and within-asset restrictions. The identification leverages three aspects: (1) the direction of a shock on Treasury yields, corporate yields, and stock return, (2) the propagation of a shock through the yield curve, and (3) the transmission of a shock through the credit spread across credit ratings.

2.2.1 Growth shocks

Growth shocks refer to changes in investors' expectations about the future growth rate of cash flows in the economy. The well-documented propagation of shocks to growth expectations has significant effects on Treasury yields and stock prices through the cash flow news channel and indirectly through the discount rate news channel. A positive shock to growth expectations tends to raise Treasury yields and stock prices if cash flow news dominates (Cieslak and Pang, 2021). This effect is analyzed using a model that combines a forward-looking Taylor rule—where interest rates adjust based on economic conditions—with asset pricing models that capture investor expectations. Under specific conditions, such as when the intertemporal substitution effect dominates the wealth effect (the elasticity of intertemporal substitution (EIS) is greater than one), growth shocks will lead to higher yields and stock prices, and the impact on yields weakens as maturity increases (also see Balduzzi et al., 2001 and Gürkaynak et al., 2005). Accordingly, we impose the same restrictions on the growth shocks propagating to Treasury yields and stock prices, and the impact of the shocks across the yield curve decays with yield maturity.

Although numerous studies have examined the propagation of growth shocks in Treasury and equity markets, their impact on corporate bond yields remains ambiguous and relatively

underexplored. Since corporate bonds share characteristics with both Treasuries and stocks, their response to these shocks warrants further investigation. [Gkougkousi \(2014\)](#) examines the relation between aggregate earnings changes and corporate bond market returns, finding that aggregate earnings changes have a negative relation to investment-grade corporate bond prices and a positive relation to high-yield corporate bond prices. However, the response of corporate bonds to growth shocks can be influenced by central bank policies, risk premiums, and market sentiment. [Krishnamurthy and Vissing-Jorgensen \(2011\)](#) argue that a low growth shock, which may lead to the expectations of a looser monetary policy, can benefit high-yield bonds by decreasing the cost of borrowing and improving the credit outlook.⁴ Therefore, empirical analysis is needed to establish the precise direction and magnitude of the impact. Our analysis will rely on data to empirically identify the direction and magnitude of the impact, allowing us to understand the sign and significance of the relationship between growth shocks and corporate bond yields.

2.2.2 Monetary shocks

In this paper, a monetary shock is defined as an exogenous innovation to the short-term risk-free interest rate or its anticipated future path, which is orthogonal to other state variables driving the short rate. Unlike previous literature, which predominantly identifies monetary shocks as deviations from the systematic monetary policy described by the Taylor rule, we adopt a more inclusive approach as proposed by [Cieslak and Pang \(2021\)](#). Specifically, while prior empirical studies typically rely on rapid fluctuations of short-term interest rates within narrow windows surrounding FOMC announcements to isolate monetary shocks, we assume monetary shocks can occur continuously, consistent with recent empirical evidence highlighting that Federal Reserve communications and policy-related news regularly emerge beyond announcement periods ([Cieslak and Schrimpf, 2019](#)).

Many studies demonstrate that monetary shocks embody the discount rate effect. That

⁴[Krishnamurthy and Vissing-Jorgensen \(2011\)](#) find that QE policies can lower yields across the board, but the effects are particularly strong for riskier assets, including high-yield bonds.

is, a decline in the risk-free rate increases the prices of all assets, including stocks, Treasury bonds, and corporate bonds. Across maturities, the response of the two-year Treasury yield is generally found to be approximately two to three times greater than that of the ten-year Treasury yield. (e.g., [Bernanke and Kuttner, 2005](#); [Campbell et al., 2012](#); [Gürkaynak et al., 2005](#); [Rigobon and Sack, 2004](#); [Cieslak and Schrimpf, 2019](#)). In line with these empirical findings and consistent with [Cieslak and Pang \(2021\)](#) and [Neal et al. \(2015\)](#), we posit that a rise in monetary shocks drives lower stock and bond prices. Additionally, the impact of these shocks on Treasury yields declines across maturities.

2.2.3 Risk premium shocks

To examine the economic shocks influencing the aggregate stock market and the Treasury yield curve, [Cieslak and Pang \(2021\)](#) introduce a novel two-factor structure in risk premia: common and hedging premium shocks. Common premium shocks drive the prices of both stocks and Treasuries in the same direction, whereas hedging premium shocks cause these prices to move in opposite directions. This two-factor structure effectively captures the dynamic comovement between stock returns and Treasury yields over time. This paper extends the conventional two-factor framework for risk premia to a three-factor structure by incorporating a default premium shock, thereby characterizing the joint dynamics and comovement of stock returns and bond yields.

The risk premium shocks affect the longer end of the yield curve more strongly than the short end (e.g., [Cieslak and Pang, 2021](#)). Common premium shocks drive stock and bond prices in the same direction—a positive shock decreases stock prices and increases Treasury and corporate bond yields. Hedging premium shocks drive stock and Treasury bond prices in different directions—a positive shock decreases stock prices and Treasury yields. The impact of hedging premium shock on corporate bond yields is less clear. Corporate bonds straddle the characteristics of both Treasury bonds and stocks. Like Treasuries, they are influenced by interest rates and macroeconomic conditions, but they also carry credit risk

and exhibit sensitivity to economic conditions, similar to stocks. This dual characteristic requires a nuanced approach to understanding how risk premium shocks impact corporate bond yields, integrating insights from fixed-income and equity market analyses. Recognizing these similarities and differences is essential for accurately modeling and predicting the behavior of corporate bonds in response to risk premium shocks. We consider two categories of corporate bonds: investment-grade bonds and high-yield bonds. The investment-grade bonds exhibit characteristics more closely aligned with Treasury bonds, while high-yield bonds resemble stocks. This perspective is supported by empirical findings from [Baker et al. \(2012\)](#) and [Gkougkousi \(2014\)](#). While [Baker et al. \(2012\)](#) examine comovement from the perspective of equities—showing that government bonds tend to comove more with ‘bond-like’ stocks (i.e., large, low-volatility, profitable, and dividend-paying firms)—our analysis takes a complementary approach by focusing on the corporate bond side. We propose that stocks are more likely to comove with ‘stock-like’ corporate bonds, such as high-yield bonds, whereas Treasury bonds are more closely aligned with ‘Treasury-like’ corporate bonds, such as investment-grade bonds. Therefore, we restrict that the hedging premium shock negatively affects investment-grade bond yields while positively affecting high-yield bond yields. This restriction helps characterize the empirical regularity of flight-to-quality behavior.

Default risk is fundamental to understanding corporate bond yields and stock returns because it directly impacts the risk premium required by investors, influences credit ratings, affects market liquidity, and is sensitive to both macroeconomic conditions and company-specific factors. Treasury bonds are widely regarded as having minimal default risk due to several key factors, including government backing, high creditworthiness, central bank support, market perception, and significant liquidity and market depth. Consequently, we impose zero restrictions on Treasury bonds in our model, indicating that default risk does not affect Treasury bonds contemporaneously. ([Barro, 1979](#); [Sargent and Wallace, 1981](#); [Greenwood et al., 2015](#); [Hall and Sargent, 2011](#)). Additionally, the sensitivity of corporate

bond yields to default risk shocks is assumed to increase monotonically with declining credit quality. Specifically, bonds with lower credit ratings, indicative of higher default risk, exhibit greater responsiveness to innovations in default premia. This assumption is consistent with structural credit risk models (e.g., [Merton, 1974](#)) and supported by empirical evidence (e.g., [Giesecke et al., 2011](#); [Friewald et al., 2014](#)).

2.2.4 Summary of identification restrictions

Using the $+/-$ signs to denote the same/opposite direction of impact of a positive structural shock, $*$ to denote the unknown impact direction and 0 as no impact, our identification restrictions can be summarized in the following matrix of instantaneous responses of asset prices to structural shocks ($\hat{C}$):

$$\begin{aligned} \hat{C} &= \begin{pmatrix} + & + & + & - & 0 \\ + & + & + & - & 0 \\ * & + & + & - & + \\ * & + & + & + & + \\ + & - & - & - & - \end{pmatrix} \\ &= \begin{pmatrix} C_{y_2}^g & C_{y_2}^m & C_{y_2}^c & C_{y_2}^h & C_{y_2}^d \\ C_{y_{10}}^g & C_{y_{10}}^m & C_{y_{10}}^c & C_{y_{10}}^h & C_{y_{10}}^d \\ C_{y_{IG}}^g & C_{y_{IG}}^m & C_{y_{IG}}^c & C_{y_{IG}}^h & C_{y_{IG}}^d \\ C_{y_{HY}}^g & C_{y_{HY}}^m & C_{y_{HY}}^c & C_{y_{HY}}^h & C_{y_{HY}}^d \\ C_s^g & C_s^m & C_s^c & C_s^h & C_s^d \end{pmatrix} \begin{pmatrix} \sigma_g & & & & \\ & \sigma_m & & & \\ & & \sigma_c & & \\ & & & \sigma_h & \\ & & & & \sigma_d \end{pmatrix} \end{aligned} \quad (5)$$

It is clear that zero and sign restrictions successfully distinguish η_d from other shocks. But they do completely distinguish η_g from η_h and η_m from η_c . This separation could be achieved by imposing additional conditions on how shocks propagate along the yield curve and credit rating. The within-asset restrictions involve treasury yields at different maturities

and corporate yields at different credit ratings and are imposed on elements of $\hat{C}$. Given that all the σ s are strictly positive, imposing within-asset restrictions on $\hat{C}$ is equivalent to imposing them on C .

Following [Cieslak and Pang \(2021\)](#), we posit that growth and monetary shocks drive the short end of the yield curve more than the long end of the yield curve :

$$|C_{y2}^g| > |C_{y10}^g|, |C_{y2}^m| > |C_{y10}^m| \quad (6)$$

Common and hedging premium shocks drive the short end of the yield curve less than the long end of the yield curve :

$$|C_{y2}^c| < |C_{y10}^c|, |C_{y2}^h| < |C_{y10}^h| \quad (7)$$

In addition, we posit that default premium shock exerts a stronger impact on high-yield bonds than investment-grade bonds:

$$|C_{yIG}^d| < |C_{yHY}^d| \quad (8)$$

The combination of sign, zero, and within-asset restrictions ensures a clear and economically meaningful identification of the five structural shocks, resulting in well-behaved and interpretable impulse responses..

3 Data and Empirical Method

3.1 Data description

We collect daily zero-coupon Treasury yields from [Gürkaynak et al. \(2007\)](#) published on the Federal Reserve Board website. Daily investment-grade and high-yield corporate bond yields are from Bloomberg. We obtain daily cum-dividend stock market returns on

the value-weighted portfolio of S&P 500 index from the Center for Research in Security Prices (CRSP). The real GDP growth data and survey forecast updates of real GDP growth expectations are obtained from the Federal Reserve Bank of Philadelphia. We obtain non-farm payroll announcement data (actual and expected) from Bloomberg.

The sample spans from August 2000 to December 2023. On one hand, daily corporate bond data starts from August 2000, while other data has longer availability. On the other hand, the literature shows evidence that the Federal Reserve changed its policy in the early 1980s, switching to a target interest rate (e.g., [Clarida et al., 2000](#); [Thornton, 2006](#)). Since monetary shock is one of the components we are interested in, our empirical analysis focuses on the post-2000 time period.

3.2 Estimation approach

Consider a five-variable VAR model:

$$z_t = (\Delta y_{2,t}, \Delta y_{10,t}, \Delta y_{IG,t}, \Delta y_{HY,t}, s_t), \quad (9)$$

where $\Delta y_{2,t}$ and $\Delta y_{10,t}$ represent daily changes in two-year and ten-year Treasury yield, respectively, characterizing yield curve, $\Delta y_{IG,t}$ and $\Delta y_{HY,t}$ represent daily changes in investment-grade and high-yield corporate bond yield, respectively, defining credit quality, and s_t represents daily stock market returns. Elements of z_t are demeaned before estimating the VAR. The lag length of one is determined according to the Bayesian information criterion (BIC). There are no material changes in the identified economic shocks if more lags are included. We obtain reduced-form innovations from the VAR(1) estimation.⁵

Given the innovations (residuals), u_t , from the reduced-form VAR, equation (4) exhibits

⁵The return innovation is mainly driven by the innovation of the price-dividend ratio, particularly at the daily frequency. Using log stock returns instead of changes in the log price-dividend ratio is reasonable and inconsequential for our results. At the daily frequency, the noise stemming from the $(d_{t+1} - E_t(d_{t+1}))$ term can be assumed negligible given the smooth dynamics of aggregate dividends. We verify that using either with-dividend returns or capital gains on S&P 500 index leads to essentially identical identified shocks and stock return decompositions.

that u_t is a linear combination of all structural shocks, η_t . However, these linear combinations are not unique; there are many possible combinations. Some of these combinations yield impulse responses with the correct postulated signs, while others do not. The essence of sign restrictions is to select the correct combinations that ensure the impulse response functions align with the postulated sign information. Following [Kilian and Lütkepohl \(2017\)](#) and [Cieslak and Pang \(2021\)](#), we begin by first estimating the variance-covariance matrix Ω_t of closed-form VAR residuals, u_t . Then we apply a Cholesky decomposition to obtain $\omega_t = P^{-1}u_t$, where P is the lower triangular matrix, $\Omega_u = PP'$, and ω_t are contemporaneously uncorrelated. Now we form the combinations by introducing an orthonormal rotation matrix Q_i , that is $u_t = PQ_i'Q_i\omega_t$. Let $\eta_t = Q_i\omega_t$. Notice that $cov(\eta_t\eta_t') = I$. Using the approach of [Rubio-Ramirez et al. \(2010\)](#), we construct the rotation matrices Q_i based on the QR matrix factorization of randomly drawn orthogonal matrices from a uniform distribution. We obtain and store 2,000 valid solutions for which $\hat{C}(Q_i) = PQ_i'$ satisfies the restrictions laid out in section 2.2.4, and base our subsequent analysis on this set.

We consider the median target (MT) solution following [Fry and Pagan \(2005, 2011\)](#) and [Cieslak and Pang \(2021\)](#) to represent instantaneous asset price responses to structural shocks. For each $Q_i \in R$, we denote the vector of instantaneous responses as $\pi_i = \text{vec}(\hat{C}(Q_i))$. We then standardize each solution, π_i , by subtracting the element-wise median and dividing by the standard deviation, both measured over the set of models that satisfy identification restrictions:

$$\pi_{MT} = \min_i \left[\frac{\pi_i - \text{median}(\pi_i)}{\text{std}(\pi_i)} \right]' \left[\frac{\pi_i - \text{median}(\pi_i)}{\text{std}(\pi_i)} \right] \quad (10)$$

Figure 1 displays the cumulative paths and expanding window sums of daily shocks. We superimpose paths from the MT solution as well as the median of cumulative shocks across all retained solutions. The two paths closely overlap and capture all recession periods with decreasing growth shocks and increasing risk premium shocks, revealing intuitive business cycle properties. They also reflect several well-known features of the US data, including the spikes in risk premium during the Great Financial Crisis and the COVID-19 pandemic, the

stable recovery after recessions, and smooth monetary shocks during zero lower bound zones.

3.3 Asset price responses to shocks and variance decompositions

In this section, we focus on the asset price impulse responses and the relative importance of identified shocks. We examine how much each economic shock has driven the overall variation in Treasury yields, corporate yields, and stock returns since 2000 and assess the dynamics of these shocks over time.

3.3.1 Impulse responses to identified shocks

Since our VAR uses daily data, directly inferring the long-run effects of shocks may raise concerns. To examine persistence more reliably, we adopt the local projections method proposed by [Jordà \(2005\)](#) and [Cieslak and Pang \(2021\)](#). This approach is particularly useful given the well-known econometric challenges associated with estimating mean reversion in asset prices using VARs. We regress treasury yield changes, corporate yield changes, and stock returns over various horizons on our identified shocks:

$$Y_{t+h}^j - Y_{t-1}^j = \alpha_h + \beta_h^{j'} \eta_t + \kappa_{t-1,t+h} \quad (11)$$

Horizon h is measured in business days. The coefficient matrix $\beta_h^{j,i}$ measures the impact of a one-standard-deviation shock of η_i on yield changes or log stock returns over $h+1$ days. By tracing out the elements of β_h as functions of h , we derive the cumulative impulse-response functions.⁶ We examine the impulse responses over horizons of up to 800 business days. The estimation is conducted using the 2000–2023 sample, with the results reported in [Figure A1](#) of the Internet Appendix. The associated error bands are computed using a Newey-West covariance matrix with $h+1$ lags, treating the structural shocks from the MT solution as given.

⁶We emphasize that the identification assumptions apply solely to the contemporaneous responses of shocks at impact ($h=0$), while leaving the responses for $h>0$ entirely unconstrained.

Growth shocks lead to positive movements in both Treasury bond yields and stock returns, with effects that gradually mean-revert over time. While the positive, mean-reverting responses of Treasury bond yields and stock returns to growth shocks are consistent with prior literature (e.g., [Cieslak and Pang \(2021\)](#)). We also find that growth shocks exhibit relatively persistent effects on corporate bond yields. Monetary shocks exhibit economically significant effects on short-term Treasury yields. They have weak positive (negative) effects on corporate bond yields (stock returns) in short-run, consistent with the literature that interest rate shocks have small or little effects on stock returns and corporate spreads (e.g., [Campbell and Ammer, 1993](#) and [Neal et al., 2015](#)).

Common and default premium shocks tend to have weak effects on Treasury bond yields and investment-grade bond yields, but exhibit persistent effects on stock returns and high-yield bond yields. Hedging premium shock tends to persistently affect treasury and investment-grade bond yields, but has only weak effects on high-yield bond yields and stock returns. The observed responsiveness of corporate bond yields to these shocks provides a new perspective that broadens the existing body of evidence.

3.3.2 Variance decompositions

To describe the relative contributions of different shocks to the overall variance of asset prices over our sample, following [Cieslak and Pang \(2021\)](#), we calculate variance ratios as variance decompositions divided by overall variance,

$$VR_{i,j} = \frac{Var(\eta_i|u_j)}{Var(u_j)} \quad (12)$$

where u_j is the daily reduced-form residuals to asset j , $Var(u_j)$ is the overall variance of residuals to asset j , and $Var(\eta_i|u_j)$ is the variance of residuals to asset j induced by shock i . Since variance ratios may vary across different solutions within the identified set, we construct and report both the average variance ratios across all retained solutions and ratios

obtained with the MT solution. Figure A2 in the Internet Appendix demonstrates that the results are qualitatively similar.

For Treasury yields and stock returns, our variance decomposition results fall within the range reported by Cieslak and Pang (2021). Approximately 75% of the variation in the two-year Treasury yield is attributable to growth and monetary shocks, with monetary news contributing a slightly larger portion. Growth and monetary shocks contribute less than 20% to the variation in the ten-year Treasury yield, consistent with the identification restrictions between maturities. The variation in stock returns is roughly evenly split between growth and monetary shocks and risk-premium shocks. The former is primarily driven by growth shocks, while the latter is mainly dominated by default risk-premium shocks. Risk-premium shocks also constitute nearly 70% and 80% of variations in investment-grade and high-yield corporate yields, respectively. The variance ratios also help to understand the decoupling between assets. Hedge shocks contribute roughly 30%, 50%, 35%, and 15% of variations in two-year Treasury yields, ten-year Treasury yields, corporate yields, and stock returns.

4 Asset Price Responses to Monetary Policy and Macro News

We now proceed to the primary empirical application of our approach. Since the identified shocks are innovations relative to the information set of investors, we can assess the information content of significant economic events as perceived by investors in real time. To explore the underlying economic drivers of asset price fluctuations in key economic events, we adopt the historical decomposition methodology of Cieslak and Pang (2021). This approach enables us to quantify the contribution of each structural shock to daily changes in asset prices. For each day t , we decompose the observed price changes in each asset into components attributable to the five shocks, denoted as $z_t(\eta_i) = \sum_{k=0}^{t-2} \Phi_z^k \hat{C} D_{ii} \eta_{t-k}$, where D_{ii} is a square matrix with (i, i) -th element equal to one and zeros elsewhere. The overall

log stock return or yield change is reconstructed by summing across the shocks, $\sum_i z_t(\eta_i)$.⁷ Since returns and yield changes are demeaned, the decomposition measures how each shock contributes to deviations from the unconditional mean, offering a structural lens into the sources of asset price movements over time.

We rely on this decomposition to analyze how business cycle conditions and major economic announcements — FOMC meetings and non-farm payroll releases — drive asset price movements and comovements. First, we examine the behavior of asset prices and their comovements across different phases of the business cycle. Then, we analyze how asset prices respond to key economic events and how investor behavior varies across macroeconomic conditions.

4.1 Asset price responses across business cycles

Asset prices exhibit dynamic responses during business cycles, reflecting the complex interplay between economic conditions, time-varying risk, market sentiments, and policy interventions. The macro-finance literature asserts that financial factors do not exert a constant influence on the economy; instead, their impact is elusive and episodic in nature, depending on specific economic episodes (e.g., [Davig et al., 2010](#) and [Hubrich and Tetlow, 2015](#)).

We measure the state of the economy using the Chicago Fed National Activity Index (CFNAI).⁸ Federal Reserve Bank of Chicago constructs the CFNAI based on 85 economic indicators, and CFNAI provides a broad, high-frequency measure of real economic activity. A high value of CFNAI implies that the national economy expands at its historical trend (average) rate of growth. We distinguish between bad and good economic times by dividing the CFNAI values at their sample median, classifying observations below the median as

⁷For a detailed exposition of the historical decomposition framework, see [Cieslak and Pang \(2021\)](#), Section 3.4.

⁸We use the CFNAI to distinguish economic states because it offers a continuous, timely, and high-frequency measure of economic activity, while NBER business cycle dates are retrospective and published with a lag. Nonetheless, we also conduct robustness checks using NBER recession dates and find qualitatively similar results; these are available upon request.

bad times and those above as good times.⁹ We regress asset price changes/shock-related components on a bad time dummy variable (D_{bad}):

$$z_t^j / z_t^j(\eta_i) = \gamma_0 + \gamma D_{bad,t} + e_t \quad (13)$$

where $z_t = (\Delta y_{2,t}, \Delta y_{10,t}, \Delta y_{IG,t}, \Delta y_{HY,t}, s_t)$, and $z_t^j(\eta_i)$ denotes the component of the price change in asset j due to shock i .

Table 1 presents the ambiguous response of yield changes in Treasury bonds and corporate bonds, and stock returns across economic conditions, along with the contributions of individual structural shocks. Decomposing asset price changes into their structural components provides additional insights into the driving forces behind these dynamics. Our empirical results confirm several stylized facts about asset price dynamics and comovements during business cycles and reveal some novel findings.

Recessions are associated with a significant decline in two-year Treasury yields (-0.377 bps, $t = -2.68$), whereas ten-year Treasury yields show a smaller and statistically insignificant decline (-0.042 bps, $t = -0.27$). The larger decline in short-term yields is driven by growth and monetary shocks, whereas the muted response of long-term yields reflects an offsetting effect—positive contributions from risk premium shocks largely cancel out negative contributions from growth and monetary shocks. This aligns with evidence that central banks respond aggressively to recessions via easing monetary policy (lowering interest rates and increasing money supply), thereby exerting downward pressure on short-term bond yields (Bernanke and Blinder, 1992).

High-yield corporate bonds react positively and significantly to recessions (0.533 bps, $t = 2.41$) while investment-grade bonds show little and statistically insignificant change

⁹This median-split approach has been widely employed in empirical studies for regime classification: Ang and Bekaert (2002) use the median of macroeconomic variables to distinguish between high- and low-regime states in modeling regime switches in interest rates; Petkova and Zhang (2005) classify business conditions by splitting macroeconomic variables at their medians to examine the conditional risk premia of value and growth stocks; and Ludvigson et al. (2021) employ median thresholds of economic indicators to separate expansions from contractions when studying the relationship between uncertainty and business cycles.

(0.031 bps, $t = 0.22$). Similar to ten-year Treasury bonds, the insignificant yield changes in investment-grade bonds result from the offsetting negative effects of growth and monetary shocks versus the positive effects of risk premium shocks. In contrast, the significant and positive increase in high-yield bond yields is dominated by risk premium shocks, especially common and default premium shocks, consistent with the previous studies showing that corporate bond spreads widen during recessions due to rising credit risk and liquidity constraints (Gilchrist and Zakrajšek, 2012; He and Krishnamurthy, 2013).

Stock returns experience a significant decline (-5.778 bps, $t=-1.81$) during the bad times, confirming the well-documented relationship between economic downturns and equity market contractions (Campbell and Cochrane, 1999; Fama and French, 1993). The decline of stock returns is primarily driven by the negative impacts of growth shocks (-4.212 bps, $t = -2.01$) and risk premium shocks (-3.818 bps, $t = -1.73$). This suggests that deteriorating macroeconomic conditions lower expected corporate cash flows, heighten risk aversion, and increase the demand for risk compensation (e.g., Bekaert et al., 2009 and Ang and Bekaert, 2007). Monetary shocks (2.251 bps, $t= 2.18$) significantly and positively contribute to stock returns, suggesting that expansionary central bank interventions—such as lower interest rates and quantitative easing—help mitigate stock market declines (e.g., Bernanke et al., 1999 and Ang and Bekaert, 2007). These results underscore the countercyclical nature of monetary policy and its stabilizing effect on financial markets during economic contractions. However, the estimated effect of the hedging premium component (-0.625 bps, $t=-0.56$) is statistically insignificant, indicating that, on average, hedging premium shocks do not exert a systematic influence on stock returns during bad times. This result suggests that not all economic downturns are characterized by elevated hedging demand. Instead, hedging premia are likely to become relevant primarily during episodes of acute financial stress—such as systemic crises—when tail risk concerns intensify and investors actively rebalance toward safe-haven assets. In less severe downturns, hedging needs may already be anticipated and incorporated into asset prices, muting their marginal impact on equity returns. This

interpretation is consistent with [Harvey et al. \(2019\)](#), who argue that while flight-to-safety behavior is evident in periods of extreme stress, its average effect on equity hedging premia across broader recessionary periods is ambiguous.

The above pattern highlights a negative comovement between safe assets (Treasuries) and riskier assets (stocks and high-yield corporate bonds) during downturns, consistent with the flight-to-safety hypothesis and expectations of monetary easing, as investors move into government bonds while central banks lower short-term interest rates to stimulate the economy ([Bernanke and Blinder, 1992](#); [Gulko, 2002](#); [Connolly et al., 2005](#); [Caballero and Krishnamurthy, 2008](#); [Greenwood and Vayanos, 2014](#); [Baele et al., 2020](#)).

4.2 Asset price responses to Federal Reserve announcements

The literature increasingly shows that the Fed significantly influences asset prices through various channels. The conventional perspective is that the Fed’s policy transmission operates through the monetary news channel, where the Fed communicates the current stance or future direction of monetary policy via exogenous shocks to short-term interest rates.(e.g., [Hanson and Stein, 2015](#)). Fed may influence asset prices through other channels: the growth news channel (information channel), whereby the Fed reveals news about the state of the economy(e.g., [Nakamura and Steinsson, 2018](#); [Bauer and Swanson, 2020](#)), and the risk-premium news channel, whereby it influences the risk and the price of risk perceived by investors (e.g., [Gilchrist and Zakrajšek, 2013](#); [Cieslak and Pang, 2021](#)). The above transmission channels align with our identified growth, monetary, and risk premium shocks. This alignment enables us to systematically assess and compare the relative importance of each channel within our unified analytical framework, offering a comprehensive understanding of how these factors drive the dynamics of asset prices and their comovements.

4.2.1 News on FOMC meeting days

Lucca and Moench (2015) present intriguing yet puzzling findings that stocks earn high excess returns in the days leading up to scheduled Federal Open Market Committee (FOMC) announcements, while Treasury yields show mixed changes. They refer to this as the pre-FOMC puzzle, which standard asset pricing theories struggle to explain. Subsequent studies have explored this puzzle, providing insights into the factors behind these pre-FOMC stock drifts. Cieslak and Pang (2021) find that the high stock returns and minimal changes in Treasury yields on FOMC announcement days are driven by Fed-induced reductions in risk premium shocks. Erdemlioglu et al. (2023) propose that systemic tail risk induced by the Fed could help explain the stock returns observed before FOMC announcements.

Following Cieslak and Pang (2021), we utilize daily close-to-close stock returns and yield changes, as they capture the majority of the effects highlighted by Lucca and Moench (2015).¹⁰ We run a similar regression as equation (13). The only difference is that we replace the bad time dummy with FOMC announcement day dummy ($D_{FOMC,t}$), which is equal to one on the scheduled FOMC meeting days and zero otherwise.¹¹

We focus on the estimated coefficient γ , indicating the average effect (direction) of Fed news on asset prices.¹² The estimated coefficient γ and t-statistics in parentheses are reported in Table 2. Consistent with previous evidence (e.g., Lucca and Moench, 2015 and Cieslak and Pang, 2021), we find insignificant changes in two-year Treasury yields (-0.460 bps, $t = -1.49$). In contrast to previous findings, our results show that the ten-year Treasury yields exhibit a more pronounced and statistically significant decline (-0.750 bps, $t = -2.19$),

¹⁰Our post-2000 sample is consistent with much recent literature that the Fed started making public announcements of its decisions in 1994. Before 1994, there remained uncertainty about the timing of when the Fed's decisions reached financial markets (Thornton, 2006).

¹¹We only consider scheduled FOMC announcements to focus on the days that are less likely to be tainted by other news. Unscheduled FOMC announcements are usually interpreted as the response to unexpected events from the Fed (e.g., Bernanke and Kuttner, 2005), and may not reflect conventional monetary news.

¹²As a robustness check, we show that monetary shocks are significantly more volatile (22.6% higher absolute magnitude) on scheduled FOMC announcement days compared to other days (see Table A1 in the Internet Appendix).

indicating that Treasury bonds with longer maturities are more responsive to the Fed’s policy signals than those with shorter maturities. Turning to corporate bond markets, investment-grade corporate bond yields fall significantly by 0.805 basis points ($t = -2.65$), while high-yield corporate bond yields exhibit a smaller and statistically insignificant decline of 0.332 basis points. These results suggest that highly rated credit instruments may benefit more from the Fed’s policy announcements than speculative-grade bonds, possibly reflecting differential exposure to perceived changes in macroeconomic or financial risk. Stock returns exhibit a statistically significant and economically large increase of 18.1 basis points ($t = 2.58$) on average, suggesting that equity markets respond positively to Federal Reserve communications. This result is consistent with the literature documenting abnormal stock returns around FOMC meetings (e.g., [Lucca and Moench, 2015](#) and [Cieslak and Pang, 2021](#)).

A decomposition of these effects into individual economic shocks reveals distinct transmission channels for different asset classes. Growth and monetary shocks have an insignificant effect on stock returns and yield changes, suggesting that FOMC meetings are less likely to systematically convey positive or negative information about the economic outlook in our sample. [Bauer and Swanson \(2020\)](#) show that the Federal Reserve has improved its communication strategy, leading to fewer surprises in monetary policy announcements since the mid-1990s.¹³

Instead, the observed changes in asset prices are primarily driven by risk premium shocks, particularly for ten-year Treasury yields, investment-grade corporate bond yields, and stock returns. The decomposition of asset price changes reveals that the common premium shock significantly contributes to the declines in ten-year Treasury yields and investment-grade corporate bond yields, and the increase in stock returns, suggesting a reduction in the risk premium during FOMC announcements.¹⁴ The default premium shock contributes

¹³Alternatively, monetary policy shocks may not convey new or informative signals beyond what is already priced into markets. It is also plausible that the average effect of monetary shocks across announcements cancels out due to offsetting surprises in different directions—tightening versus easing—resulting in muted aggregate responses.

¹⁴[Bekaert et al. \(2013\)](#) emphasize the role of risk sentiment in shaping bond term premia.

to a significant decline in investment-grade corporate bond yields (-0.386 bps) while simultaneously generating a significant increase in stock returns (15.515 bps), indicating that FOMC announcements attenuate investor perceptions of market uncertainty and risk. The positive price response of equities and corporate bonds to FOMC announcements can be understood through the default risk channel. Accommodative monetary policy and dovish guidance reduce refinancing pressures and borrowing costs, improve liquidity conditions, and strengthen expectations of economic support. These effects lower the perceived probability of default and required risk premia, thereby raising valuations for corporate bonds and equities alike (see [Gertler and Karadi, 2015](#); [Gilchrist et al., 2015](#)).¹⁵

4.2.2 News on FOMC meeting days during bad and good times

Macro finance studies highlight that investor sensitivity to monetary policy announcements is state-dependent, with financial markets reacting more strongly during periods of heightened uncertainty or economic stress (e.g., [Boyd et al., 2005](#) and [Hesse et al., 2018](#)). To empirically examine the state-contingent effects of monetary policy communications, we investigate how asset price changes and their shock-related components respond to scheduled FOMC announcements under varying economic conditions.

To capture the broader economic environment in which the news arrives, we measure the state of the economy using the CFNAI as described in section 4.1. We estimate the following regression model, which interacts the FOMC announcement day dummy with the bad time dummy:

$$z_{k,t}/z_{k,t}(\eta_i) = \alpha + \beta D_{FOMC,t} + \gamma D_{bad,t} + \delta D_{FOMC,t} * D_{bad,t} + e_t \quad (14)$$

Equation (14) enables a clear decomposition of the total effect of FOMC announcements in each state. For example, $\beta + \delta$ (β) captures the marginal effect of FOMC announcement during bad (good) times, while $\gamma + \delta$ (γ) captures the marginal effect of bad times on FOMC

¹⁵We note that the response in high-yield corporate bonds is more muted. Our findings align with the literature emphasizing the central role of risk-premium adjustments in the transmission of monetary policy to equity markets ([Bernanke and Kuttner, 2005](#); [Cieslak and Pang, 2021](#)).

(non-FOMC) days.¹⁶

We first examine the marginal effect of FOMC announcements in each state (β vs $\beta + \delta$). Table 3 provides compelling evidence that the effects of Federal Reserve communications on financial markets are highly state-dependent, both in magnitude and in the underlying economic mechanisms through which they operate. The estimated β coefficients are 0.115 ($t = 0.26$), 0.114 ($t = 0.23$), 0.040 ($t = 0.09$), -0.104 ($t = -0.15$), and 13.077 ($t = 1.30$), corresponding to changes in two-year Treasury yields, ten-year Treasury yields, investment-grade bond yields, high-yield bond yields, and stock returns, respectively. None of these estimates is statistically significant, suggesting that FOMC communications have no statistically detectable effect during good times. The evidence indicates that the marginal effect of FOMC announcements on stock returns, as shown in prior studies (e.g., [Lucca and Moench, 2015](#) and [Cieslak and Pang, 2021](#)), is not evident during good times in our setting.

The estimates of $\beta + \delta$ are -1.002 (p-value = 0.02), -1.573 (p-value = 0.00), -1.612 (p-value = 0.00), -0.559 (p-value = 0.41), and 23.006 (p-value = 0.02), corresponding to the same set of asset classes in the order listed above. In contrast to the marginal effect observed in good times, in bad times, FOMC announcements elicit strong and statistically significant reactions across Treasury yields, corporate bond yields, and stock returns.¹⁷ While previous studies have largely documented marginal effects of FOMC announcements on stock returns, our evidence uncovers a broader, state-dependent transmission mechanism, highlighting an asymmetric effect of FOMC announcements. During adverse conditions, FOMC communications exert both stronger and more pervasive effects across multiple asset classes. These results complement earlier findings that central bank signals have diminished influence when uncertainty is low and policy actions are anticipated (e.g., [Lucca and Moench, 2015](#)), and are consistent with theoretical predictions that market sensitivity to policy is attenuated in expansions when risk premia and uncertainty about fundamentals are reduced

¹⁶See Table A2 in the Internet Appendix for a detailed discussion of the scenario-based mapping of the regression specification.

¹⁷Notably, the response in high-yield bonds remains muted, suggesting segmentation in credit markets.

(e.g., [Vayanos and Vila, 2021](#)).

The contributions of individual shocks to the marginal effects of FOMC announcements offer deeper insight into the underlying economic drivers of these effects. First, we find that the marginal effects of growth shocks and monetary shocks have little asymmetric impact on all yield changes and stock returns. None of the coefficients, β^m , β^g , $\beta^m + \delta^m$, or $\beta^g + \delta^g$, is statistically significant, suggesting that the transmission of monetary policy surprises to yields and returns shows little evidence of state-dependent amplification in our sample. Second, the asymmetric effect of FOMC announcements is primarily driven by risk premium shocks, suggesting that in bad times, these announcements may help mitigate economic and market uncertainties, reassure investors about the economic outlook, and reduce the required risk compensation. Third, the insignificant asymmetric effect of FOMC in bad times for high-yield bonds is mainly due to the offsetting influence between common and hedging premium shocks.

We next consider the marginal effect of economic conditions conditional on the presence or absence of FOMC announcements (γ vs $\gamma + \delta$). The joint estimates of $\gamma + \delta$ are -1.432 (p-value = 0.02), -1.636 (p-value = 0.01), -1.529 (p-value = 0.01), 0.104 (p-value = 0.91), and 3.571 (p-value = 0.79) corresponding to changes in two-year Treasury yields, ten-year Treasury yields, investment-grade bond yields, high-yield bond yields, and stock returns, respectively. These results exhibit that, compared to FOMC announcements during good times, FOMC announcements in bad times are associated with higher prices for safer assets (Treasury and investment-grade bonds), but have negligible effects on riskier assets (high-yield bonds and stocks). Our results from the decomposition of shocks indicate that the declines in Treasury and investment-grade bond yields are largely attributable to reduced risk premium shocks, particularly hedging premium shocks. In contrast, the muted responses of high-yield bonds and equities arise from an offsetting pattern, where the negative impact of hedging premium shocks is counterbalanced by the positive influence of common and default premium shocks.

The coefficient γ captures the different market responses across economic states on

non-FOMC announcement days. The estimates show that, in bad times relative to good times, two-year Treasury bond yields decline (-0.315 , $t = -2.17$), high-yield bond yields increase (0.558 , $t = 2.45$), and stock returns decrease (-6.358 , $t = -1.94$) on non-FOMC days, while the yield changes for other bonds are statistically insignificant. Structural shock decomposition reveals that the decline in two-year Treasury yields is primarily driven by growth and monetary shocks, reflecting expectations of weaker economic prospects and accommodative policy responses. By contrast, the rise in high-yield bond yields is dominated by increased risk premium shocks, which more than offset the downward pressures from growth and monetary shocks. Similarly, the drop in stock prices is explained by the combined effects of negative growth shocks and elevated risk premium shocks, highlighting the amplified sensitivity of risky assets to deteriorating macroeconomic conditions in the absence of FOMC communications.

Our findings contribute to the literature on the asset price effects of FOMC announcements by offering several novel insights. First, while prior research (e.g., [Lucca and Moench, 2015](#); [Cieslak and Pang, 2021](#)) documents elevated stock returns around scheduled FOMC announcements with minimal movement in Treasury yields, we confirm the positive equity response and further show that ten-year Treasury note prices and investment-grade corporate bond prices also rise on FOMC announcement days, highlighting broader cross-asset effects than previously reported. Second, we provide novel evidence of state-dependent impacts: the marginal effect of FOMC announcements is concentrated in bad economic times. This evidence indicates that the FOMC is more responsive to negative macroeconomic developments during bad times. Third, we show that financial markets exhibit asymmetric reactions across economic states both in the presence and absence of FOMC announcements. These asymmetric effects underscore the state-dependent nature of asset price responses to monetary policy and shed new light on the conditional effectiveness of central bank communication.

4.3 Asset price responses to macro news

In addition to monetary policy signals, financial markets exhibit significant responses to macroeconomic news, especially when such announcements shift investors' expectations regarding future growth, inflation, or risk. However, interpreting the asset price responses to macroeconomic announcements is inherently complex due to the multifaceted informational content of these releases. [Boyd et al. \(2005\)](#) and [Elenev et al. \(2024\)](#) document that stock market responses to macroeconomic news are state-dependent: bad news, such as rising unemployment, can lead to positive stock market reactions during expansions but negative reactions during recessions. Moreover, markets exhibit heightened sensitivity to news when the economy operates below its potential. To better understand the drivers behind these results, [Cieslak and Pang \(2021\)](#) examine how investors update their beliefs in response to macroeconomic news across different phases of the business cycle. These findings underscore that the market impact of macroeconomic news is not solely a function of the data surprise itself, but also of the broader economic context in which it arrives.

To better understand the mechanisms underlying these state-dependent responses, we examine how investors revise beliefs over the business cycle in response to U.S. non-farm payroll (NFP) announcements. NFP data releases are widely regarded as the most influential piece of scheduled macroeconomic news in the U.S., due to their timeliness and relevance for labor market conditions and monetary policy expectations (e.g., [Andersen et al., 2007](#) and [Cieslak and Pang, 2021](#)). To quantify the economic content of NFP releases, we construct NFP surprises as the difference between the actual reported payroll number and the median Bloomberg survey forecast, covering the period from 2000 to 2023. A positive surprise (actual > expected) is labeled as good news, while a negative surprise represents bad news. We define two macroeconomic regimes (bad times and good times) by splitting the CFNAI series at the median, with the lower half representing weaker economic conditions.¹⁸ This

¹⁸Compared to the unemployment gap in [Cieslak and Pang \(2021\)](#), the CFNAI provides a broader and more timely measure of economic activity by aggregating data from multiple sectors (85 monthly indicators), making it a more comprehensive and responsive indicator of macroeconomic conditions. Its

binary classification allows us to assess how investor reactions to NFP announcements differ depending on whether the news arrives in a relatively favorable or unfavorable economic environment.

Following [Cieslak and Pang \(2021\)](#), we consider a similar regression, regressing the announcement-day asset price changes onto four dummy variables reflecting the full set of interactions between NFP announcement dummies (B=bad/G=good NFP news) and economy state dummies (B=bad/G=good times):

$$z_{k,t}/z_{k,t}(\eta_i) = \gamma_1 D_{BG,t} + \gamma_2 D_{BB,t} + \gamma_3 D_{GG,t} + \gamma_4 D_{GB,t} + e_t \quad (15)$$

The first letter in subscript indicates the type of NFP news; the second letter describes the overall state of the economy (e.g., D_{BG} is a dummy variable for days with bad NFP news coming out in good times). The coefficients γ capture conditional average changes in yields and stock returns.

Table 4 provides results that asset price responses to macroeconomic news are highly conditional on both the sign of the news (positive vs. negative NFP surprises) and the prevailing macroeconomic environment (good vs. bad times). When bad NFP news arrives during good economic times (BG), consistent with previous findings that bad news in good times is perceived as good news (e.g., [Boyd et al., 2005](#) and [Cieslak and Pang, 2021](#)), stocks exhibit a significant positive return of 22.381 bps ($t = 2.09$). [Cieslak and Pang \(2021\)](#) attribute this price pattern entirely to investors updating their beliefs toward a more accommodative monetary policy stance, as only the monetary shock is found to be significant. In good times, Fed communication makes monetary tightening expected. But when bad NFP news arrives, investors may see it as a sign that the tightening cycle may end. In our setting, however, the positive stock price reaction is not driven by monetary shocks that directly shift the policy rate path. Instead, negative NFP surprises in

empirical alignment with NBER recessions further supports its use in identifying good and bad times in asset pricing studies.

good economic times appear to reduce concerns about further rate hikes, thereby lowering precautionary demand for Treasuries and compressing the hedging premium shocks. This decline in demand for safe assets prompts a reallocation toward riskier securities, leading to simultaneous increases in equity and high-yield bond prices and declines in Treasuries and investment-grade bonds. Our shock decomposition supports this mechanism. First, hedging shock is the only statistically significant driver of asset fluctuations when bad news arrives in good times. Second, the signs of the hedging shock coefficients are consistent with diminished flight-to-safety motives.

When bad NFP news is released during periods of economic weakness (BB), asset markets respond in a more synchronized and risk-averse fashion. Stocks experience a substantial and statistically significant decline of 44.471 basis points ($t = -2.24$), accompanied by moderate declines in Treasury yields: two-year Treasury yield falls by 1.280 bps ($t = -1.79$) and ten-year by 1.351 bps ($t = -1.76$). Investment-grade corporate bond yields also decline by 0.972 basis points ($t = -1.79$), whereas high-yield corporate bonds display no significant response. The decline in yields and stock returns reflects classic flight-to-safety behavior. The structural decomposition indicates that the growth shock explains the bulk of the negative yield changes and stock returns, reflecting that investors revise downward their perceptions about future economic growth, consistent with [Cieslak and Pang \(2021\)](#). This finding supports asset pricing models that emphasize the primacy of macroeconomic fundamentals (especially expected cash flows) in driving asset valuations during recessions ([Bansal and Yaron, 2004](#); [Lettau and Ludvigson, 2010](#)). The sharp equity market reaction and accompanying yield changes underscore the idea that bad news in bad times reinforces prevailing macroeconomic pessimism. It signals worsening fundamentals and leads investors to lower their expectations and move to safer assets, amplifying the effect of negative growth shocks in weak economic conditions.

In the case of good NFP news in good times (GG), asset price responses are generally weaker and less coordinated. For good NFP news in bad times (GB), however, asset price

movements are mixed, consistent with [Cieslak and Pang \(2021\)](#).

In summary, our findings indicate that asset price reactions to NFP news are highly state-dependent and vary significantly across asset classes. Bad news on NFP in good times boosts stock returns by reducing hedging risk premia, while bad news in bad times triggers broad-based declines across equity prices and bond yields, primarily driven by negative growth shocks. In contrast, good news elicits weaker and more asymmetric responses, especially during downturns, where investor optimism remains muted. We provide a novel channel that helps to explain why negative NFP news in good times can be good news for stock market.

5 Structural Sources of Asset Price Comovements

Understanding asset price comovement is fundamental to asset pricing theory and financial market analysis. Previous literature has documented that correlations between equities and government bonds are time-varying, shaped significantly by risk aversion, variations in discount rates, and flight-to-safety behavior (e.g., [Baele et al. \(2010\)](#); [Bekaert et al. \(2010\)](#); [Campbell et al., 2017](#)). Furthermore, [Gilchrist and Zakrajšek \(2012\)](#) and [Abrahams et al. \(2016\)](#) demonstrate that corporate bond spreads and equity returns exhibit common exposures to default and liquidity risk premia, underscoring the importance of disentangling risk-based channels from other macroeconomic drivers such as growth or monetary shocks.

Building on the expanding literature, we investigate the joint dynamics of asset markets by structurally decomposing the time-varying comovement among Treasury yields, corporate bond yields, and stock returns. Specifically, we attribute asset price correlations to our identified five structural shocks. To quantify these linkages, we compute the average correlations between asset price changes (negative yield changes and stock returns) and decompose these correlations into contributions from each of the five shocks over various

sample periods. Formally, the overall correlation (ρ) between asset price changes z_x and z_y can be expressed as:

$$\rho = \rho_g + \rho_m + \rho_c + \rho_h + \rho_d. \quad (16)$$

where each component ρ_i is computed as the covariance between the respective structural decompositions of asset price changes scaled by the standard deviations of the full asset price series: $\rho_i = \frac{\text{Cov}(z_x(\eta_i), z_y(\eta_i))}{\sigma_{z_x} \sigma_{z_y}}$. In addition, we report the total contribution of risk premium comovements as $\rho_{rp} = \rho_c + \rho_h + \rho_d$, capturing the extent to which time-varying risk compensation jointly affects asset prices. The analysis spans the period from August 2000 to December 2023. Specifically, we examine two key episodes of financial market turmoil: the Global Financial Crisis (GFC) from December 2007 to June 2009 and the COVID-19 pandemic from February 2020 to April 2020.¹⁹ It is well established that the Global Financial Crisis stemmed from structural vulnerabilities and breakdowns within the financial system, whereas the COVID-19 crisis was primarily a real-economy shock, triggered by abrupt disruptions to production and consumption due to the global health emergency. These distinct origins provide a unique natural experiment to investigate the underlying drivers and mechanisms of asset comovements, as financial markets responded to fundamentally different types of shocks—one rooted in the financial sector, the other in the real economy.

Table 5 reports the comovement patterns and their structural decompositions, showing that asset price comovements—and their underlying drivers—are highly time-varying and shock-dependent. Over the full sample, we observe strong and statistically significant correlations: $\rho_{(y_{10}, y_{IG})} = 0.843$, $\rho_{(y_{IG}, y_{HY})} = 0.276$, and $\rho_{(y_{HY}, y_s)} = 0.299$, alongside significant negative correlations: $\rho_{(y_{10}, y_s)} = -0.307$ and $\rho_{(y_{IG}, y_s)} = -0.146$. These findings are consistent with the flight-to-safety behavior documented in the literature (e.g., [Gulko, 2002](#)) and complement the insights from [Baker and Wurgler \(2012\)](#), who show that bond-like stocks exhibit stronger comovement with bonds. We extend this narrative by showing that stock-like

¹⁹Recession dates are based on the National Bureau of Economic Research (NBER) business cycle chronology: <https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions>.

bonds tend to comove more with equities, while Treasury-like corporate bonds tend to comove more with Treasuries, reflecting a stronger alignment in underlying asset characteristics. While prior studies attribute flight-to-safety patterns and countercyclical equity risk premia primarily to risk-premium shocks (e.g., [Gilchrist and Zakrajšek, 2012](#); [Bekaert et al., 2013](#)), our results offer a more nuanced view. Specifically, the strong positive correlations $\rho(y_{10}, y_{IG})$ and $\rho(y_{HY}, y_s)$ are mainly driven by risk-premium shocks. In contrast, the negative correlation $\rho(y_{IG}, y_s)$ is largely attributable to growth shocks, while $\rho(y_{10}, y_s)$ and $\rho(y_{IG}, y_{HY})$ reflect a more balanced contribution from both growth and risk-premium shocks.

We further examine asset yield (return) comovements during the past two major crises and uncover several notable patterns. The comovement between less risky assets, $\rho(y_{10}, y_{IG})$, weakens during crises—dropping to 0.769 in the GFC to 0.360 in the COVID-19 crisis. This decline is primarily driven by the diminished influence of both growth and risk-premium shocks. For riskier assets, the positive correlations, $\rho(y_{IG}, y_{HY})$ and $\rho(y_{HY}, y_s)$, weaken during the GFC but strengthen during the COVID-19 crisis. This divergence appears to reflect the growing role of risk-premium shocks in explaining asset comovements during the latter crisis. We also observe that the negative correlation between ten-year Treasuries and stocks, $\rho(y_{10}, y_s)$, becomes more pronounced in both crises, consistent with a flight-to-safety dynamic. In contrast, the negative correlation between investment-grade bonds and stocks, $\rho(y_{IG}, y_s)$, intensifies during the GFC and turns positive during the COVID-19 crisis. Our results indicate that growth shocks play a more prominent role during the GFC than during the COVID-19 pandemic. This finding aligns with the interpretation that, although the GFC originated from financial sector vulnerabilities, it had a substantial impact on macroeconomic expectations. In contrast, the COVID-19 crisis, primarily a real-economy shock, featured a reduced role for growth shocks—possibly due to swift and large-scale policy interventions that stabilized expectations. While comovement patterns are shaped by multiple forces, the changing importance of growth shocks across crises highlights the distinct transmission channels of each event.

These findings highlight the evolving nature of asset price comovements across crisis periods. While the correlation between less risky assets tends to be low during turbulent times, riskier assets exhibit varying degrees of integration depending on the underlying shock structure. The stronger role of risk-premium shocks during the COVID-19 pandemic, especially in driving correlations among risky assets, underscores the importance of investor sentiment and risk pricing dynamics in shaping cross-asset linkages.

6 Shock Validation

In this section, we provide supporting evidence for the credibility of our identification approach. We examine how our structural shocks relate to several observable variables that should respond if the shocks are capturing the intended economic forces. In particular, we explore their connection to monetary policy surprises measured around Fed announcements, expectations from professional economic forecasts, and proxies for risk premia drawn from financial markets. These comparisons help us assess whether the shocks we identify align with established indicators of monetary and financial conditions.

6.1 Monetary shocks with policy surprises

Monetary policy surprises are usually measured as high-frequency changes in interest rates within a narrow window of the Fed announcement. The narrow event window identification allows one to focus on the news from the Fed. However, it does not differentiate the specific type of information or news conveyed by the Fed. Accordingly, we use the term “monetary policy surprises” identified in the existing literature to align with our identification of monetary shocks. These surprises, studied in the literature, arise not only conventionally but also through information and risk-premium channels. [Campbell et al. \(2012\)](#) and [Nakamura and Steinsson \(2018\)](#) emphasize the role of the Fed telegraphing information about growth (the information effect), while [Hanson and Stein \(2015\)](#) demonstrate transmission

through shifts in risk premiums.

We derive monetary policy surprises by following the methodology of [Swanson \(2021\)](#), who disentangle changes in interest rates observed within a 30-minute window surrounding Federal Reserve announcements into two distinct components: an action surprise and a communication surprise, commonly referred to as the target and path factors, respectively. The target factor captures unexpected changes in the contemporaneous policy target rate, while the path factor reflects revisions to the expected future path of short-term interest rates—interpreted as forward guidance surprises orthogonal to the target shock—and is identified through movements in longer-term interest rates.²⁰

We regress monetary policy surprises on our structural shocks to link various surprise measures to different types of news. We report estimation results for all (only scheduled) FOMC announcements over the August 2000–June 2019 period considered by [Swanson \(2021\)](#) in panel A (B) of Table 6.

In both panels, the monetary shock loads most strongly and significantly on the target factor, while the coefficients on all other structural shocks are small and statistically insignificant at the 5% level. This is consistent with the interpretation that the target factor primarily captures the conventional policy rate surprise—an unanticipated change in the contemporaneous policy stance—rather than other forms of news. In contrast, the path factor is significantly related to all the structural shocks, implying that path monetary surprises aggregate different channels through which the Fed affects investors’ beliefs and asset prices. This result is consistent with the view that revisions to the expected future path of policy rates are not driven solely by pure monetary policy shocks, but also by information about the economic outlook ([Campbell et al., 2012](#); [Nakamura and Steinsson, 2018](#)) and changes in risk compensation ([Hanson and Stein, 2015](#)). In other words, the path factor aggregates a richer set of signals—including growth news, shifts in risk premia, and hedging demand—than the narrowly defined target factor.

²⁰The path factor does not represent a structural shock in the strict sense, as longer-term rates also incorporate macroeconomic expectations and term premia, beyond anticipated policy rates alone.

This distinction underscores the importance of our structural shock decomposition: by disentangling the different components embedded in forward guidance surprises, we can identify when asset price movements reflect conventional policy actions, and when they are driven by information or risk-premium effects, as in our BG-state NFP results.

In sum, the analysis of monetary policy surprises confirms that our identified monetary shocks are closely aligned with the target component of monetary policy surprises. At the same time, the findings highlight that Federal Reserve announcements convey a complex mix of informational content, especially their significant direct impact on beliefs about the policy path and the associated risk premium.

6.2 Growth shocks with real GDP growth/updates

Following [Cieslak and Pang \(2021\)](#) and [Duffee \(2023b\)](#), we next assess whether the growth shocks are related to macroeconomic factors and expectations. We obtain real GDP growth and its forecasts from the Survey of Professional Forecasters (SPF) at the Federal Reserve Bank of Philadelphia. We compare forecasters' expectation updates with growth shocks identified through revisions in survey forecasts. Survey revisions are not shocks in a structural sense as they reflect feedback effects between different structural factors driving macroeconomic expectations. If our identified growth shocks capture the underlying economic growth meaningfully, the survey forecasts of real GDP growth should exhibit a strong relationship to these shocks.

The SPF reports real GDP growth and its forecasts as the annualized percentage changes in the real GDP from the previous quarter. To measure forecast updates, we compute the revisions in forecasts between two consecutive surveys for the same future calendar quarter. For example, the one-quarter-ahead forecast update is defined as the difference between the forecast for quarter $t+1$ reported in survey t and the forecast for the same quarter $t+1$ reported in survey $t-1$. This construction isolates new information incorporated by professional forecasters between surveys, controlling for the forecast horizon.

Panel A of Figure 2 compares the survey updates for one quarter ahead with the identified growth shocks, both cumulated over the past 12-month period for readability of the graph. The high correlations (0.56 over the 2001–2023 sample and 0.83 over the pre-pandemic 2001–2019 sample) indicate that professional forecasters systematically revise their GDP growth expectations in the same direction as our identified growth shocks. A similar pattern emerges in panel B of Figure 2 when comparing the identified growth shocks to real GDP growth: the correlation reaches 0.53 over the full sample and 0.75 over the pre-pandemic period. This strong co-movement provides validation that the growth shocks capture meaningful news about the economic growth outlook. Notably, the correlation weakens in the full sample, as pandemic-era GDP forecast revisions were driven by unprecedented, non-financial factors that are not fully reflected in asset-price-based growth shocks.

6.3 Risk shocks with asset risk premium

In Section 2, our structural identification strategy relies on sign restrictions to characterize the effects of different shocks on asset pricing. To test and confirm these sign restrictions, we use risk premium estimates proposed in the literature. Treasury risk premia are proxied by the spread between the ten-year Treasury yield and the three-month Treasury bill rate. Corporate bond risk premia are measured as the spreads of corporate bond yields over the three-month Treasury bill rate. For equities, we adopt the forward equity premium estimates of [Martin \(2017\)](#) as a measure of the equity risk premium. All risk premium proxies are at a daily frequency.²¹

We regress innovations in these risk premium proxies on the identified structural shocks. Innovations are constructed as first differences of the risk premium series to remove persistence and isolate unexpected movements. To evaluate the role of pure risk-premium shocks, we report results both with the full set of structural shocks and with the subset of

²¹[Martin \(2017\)](#) calculates the lower bound on the forward equity premium for various horizons (from one month to one year). We report the results for the one-year premium in the main text, with robust findings for other maturities available upon request.

risk premium shocks alone. This approach offers a direct empirical assessment of whether the imposed sign restrictions on structural shocks are consistent with economically meaningful variation in risk premia, thereby supporting the validity of our identification strategy.

Table 7 reports the regression results of innovations in the Treasury bond, corporate bond, and stock risk premia on structural shocks. For all the innovations in risk premium, the estimated loadings are significant. This reflects that the risk-premium proxies are not designed to isolate purely risk-premium shocks, but also capture cash-flow-related innovations. However, across asset classes, risk-premium shocks play a dominant role in explaining yield and return variation. For the Treasury risk premium, the full set of shocks accounts for 60.2% of the variation, with risk-premium shocks alone explaining 58.1%. For investment-grade risk premium, the corresponding shares are 52.2% and 45.3%; for high-yield risk premium, 67.6% and 64%; and for equity risk premium, 64.2% and 33.9%. These results highlight that, among all shocks, risk-premium shocks consistently capture a substantial portion of asset risk premium innovations.

Additionally, the loadings of the risk premium shocks have the expected signs: positive loadings for the common premium and default risk premium shocks across all assets, and negative loadings for the hedging premium shock on safe assets (Treasury bonds and investment-grade bonds) but positive on risk assets (high-yield corporate bonds and equities). Overall, the results indicate that a significant portion of the variation in risk premium is attributable to risk-premium shocks and confirm the differentially signed impacts across the risk premium shocks.

To further validate the novel default premium shock, we compare it with an external benchmark for credit risk—the corporate credit spread constructed by [Monin \(2019\)](#), as published by the U.S. Office of Financial Research. This credit spread captures a market-based measure of aggregate credit risk across the corporate bond market. The default premium shocks are cumulated over the past 12-month period. As shown in panel C of Figure 2, the identified default premium shocks exhibit a strong positive correlation of 0.82 with

the credit spread over our sample period. This high correlation provides additional support for the interpretation of the default premium shock as capturing systematic variation in credit risk pricing. The alignment with an independently constructed credit spread index suggests that the structural shock not only reflects model-based statistical identification but also tracks empirically relevant movements in market perceptions of default risk.

7 Conclusion

This paper develops and implements a structural framework to identify the economic drivers of daily asset price fluctuations across equities, Treasury bonds, and corporate bonds. By combining sign restrictions, zero restrictions, and within-asset restrictions, we disentangle five orthogonal shocks: a growth shock, a monetary policy shock, and three distinct risk premium shocks—common, hedging, and default premium shocks. Our identification strategy provides a theoretically grounded and empirically tractable method for interpreting asset price movements through the lens of structural economic forces.

Our empirical analysis demonstrates that the responses of asset prices to macroeconomic shocks are highly state-dependent. FOMC announcements exert limited effects in strong economic conditions but play a critical stabilizing role during recessions, primarily through their influence on risk premia rather than growth expectations or monetary shocks. Similarly, market reactions to NFP announcements depend not only on the sign of the news but also on the prevailing macroeconomic state, with asymmetric responses across good and bad times.

By decomposing asset price comovements into structural components, we show that the sources of cross-asset correlation (spanning equities, Treasury bonds, and corporate bonds) are both time-varying and shock-dependent. Risk premium shocks, especially those reflecting credit and hedging considerations, play a central role in driving comovement, with their influence intensifying during periods of market stress. These findings underscore the importance of investor risk perceptions in shaping asset pricing dynamics and contribute

to the macro-finance literature by offering a unified structural framework to trace the transmission of shocks across markets and economic conditions.

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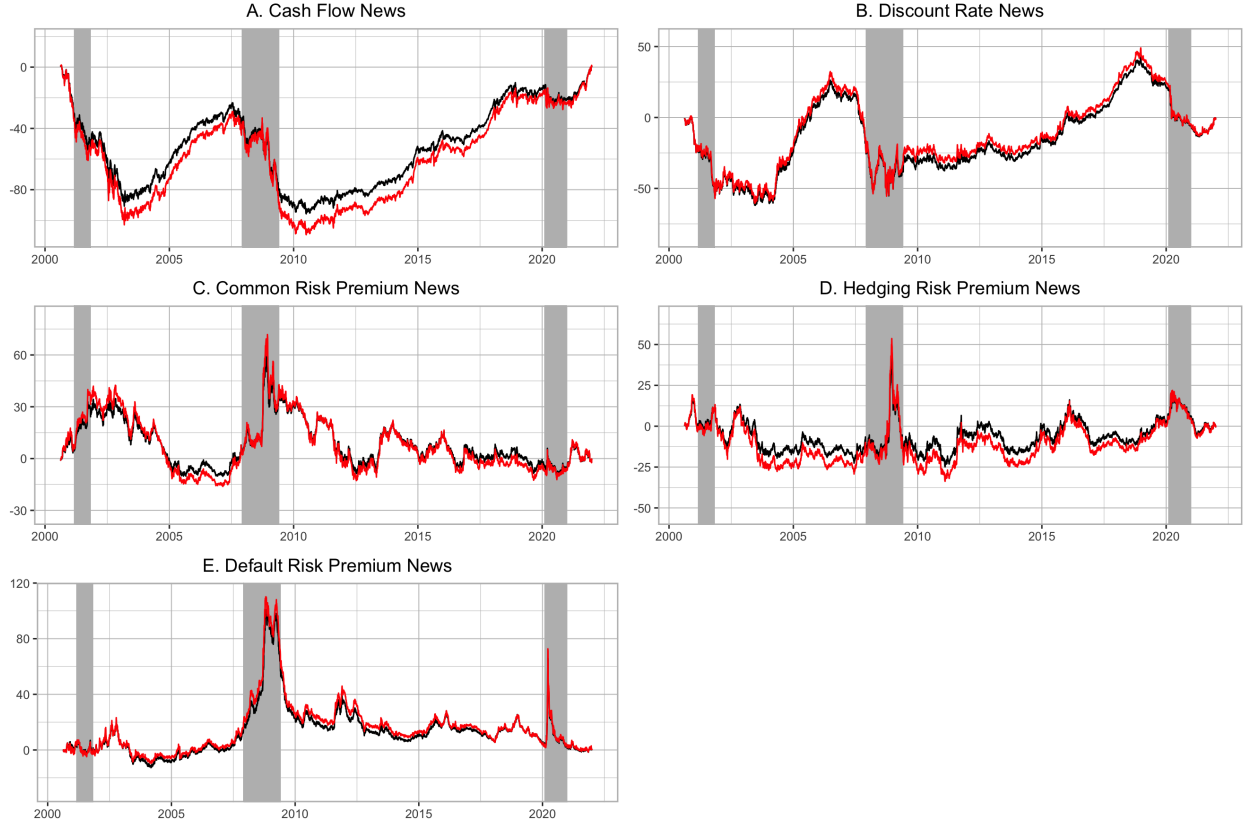


Figure 1: Paths of cumulative shocks. The figure presents paths of cumulative shocks for the MT solution (red solid) and the median of cumulative shocks (black solid) across all retained solutions. Cumulative paths are expanding window sums of daily shocks. Daily shocks are normalized to have zero mean and unit standard deviation over the sample period(2000-2021). Hence, the y-axis in the graph is expressed in standard deviation units. Paths of shocks start and end at zero by construction. The shaded areas represent NBER recession dates.

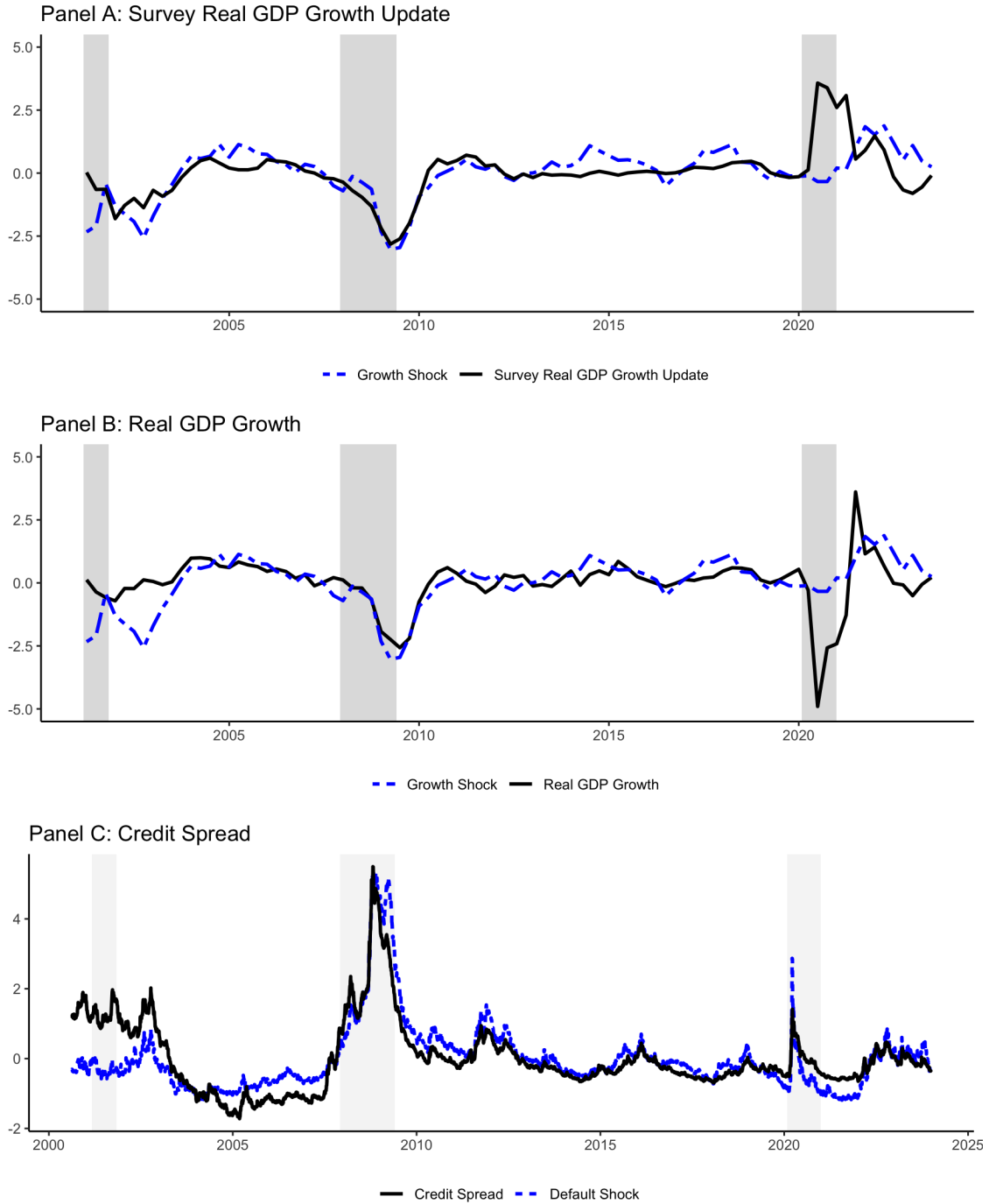


Figure 2: Comparison of identified growth and default shocks with GDP growth and credit spread. The figure superimposes identified growth shocks with real GDP growth and survey forecast updates of real GDP growth expectations from the Federal Reserve Bank of Philadelphia, and identified default risk premium shocks with credit spread estimated by [Monin \(2019\)](#) from the Office of Financial Research Website. The identified shocks, real GDP growth, and survey updates are cumulated over the past 12-month period. Survey updates are for one quarter ahead ($h = 1q$). All the variables are standardized to have zero mean and unit standard deviation. The shaded areas represent NBER recession dates.

Table 1: Regressions of yield changes or stock returns on economic conditions

This table reports the estimation results of regressions of yield changes and stock returns or their decompositions due to η shocks on the economic condition dummy. z_k represents the overall yield change or stock return. $z_k(\eta_i)$ is the historical decomposition of η_i shock to yield changes or stock returns. $z_k(\eta_{rp})$ refers to the total risk premium components (sum of the components due to η_c , η_h and η_d). The estimates are obtained as γ coefficients from the regression :

$$z_{k,t}/z_{k,t}(\eta_i) = \gamma_0 + \gamma D_{Bad,t} + e_t$$

The bad time dummy (D_{bad}) is set to one when the Chicago Fed National Activity Index (CFNAI) is below its median of our sample and zero otherwise. The first column of the table reports the class of asset (k): two-year Treasury yield changes (Δy_2), ten-year Treasury yield changes (Δy_{10}), Investment-grade corporate bond yield changes (Δy_{IG}), high-yield corporate bond yield changes (Δy_{HY}), and stock returns (s). In the regression for the second column, the dependent variable is the overall yield changes or stock returns. In the regressions presented from the third to the seventh column, the dependent variables are the historical decompositions of stock returns and yield changes into contributions of structural shocks. The last column separately reports the coefficients for the total risk premium component. t-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

k	z_k	$z_k(\eta_i)$					
		$z_k(\eta_g)$	$z_k(\eta_m)$	$z_k(\eta_c)$	$z_k(\eta_h)$	$z_k(\eta_d)$	$z_k(\eta_{rp})$
Δy_2	-0.377*** (-2.68)	-0.155** (-2.27)	-0.213** (-2.33)	0.034 (1.30)	-0.048 (-0.61)	-	-0.009 (-0.11)
Δy_{10}	-0.042 (-0.27)	-0.094** (-2.19)	-0.075*** (-2.66)	0.190* (1.92)	-0.071 (-0.65)	-	0.127 (0.86)
Δy_{IG}	0.031 (0.22)	-0.146** (-2.37)	-0.079*** (-2.77)	0.122** (2.11)	-0.036 (-0.43)	0.170** (2.57)	0.256** (2.11)
Δy_{HY}	0.533** (2.41)	-0.156** (-2.36)	-0.090*** (-3.36)	0.254** (2.50)	0.137 (1.03)	0.388*** (3.07)	0.779*** (3.74)
s	-5.778* (-1.81)	-4.212** (-2.01)	2.251** (2.18)	-0.402 (-1.26)	-0.625 (-0.56)	-2.790 (-1.50)	-3.818* (-1.73)

Table 2: FOMC meeting regression

This table reports the estimated coefficients of regressions of yield changes and stock returns or their decompositions due to η shocks on the FOMC announcement dummy (D_{FOMC}). z_k represents the overall yield change or stock return. $z_k(\eta_i)$ is the historical decomposition of η_i shock to yield changes or stock returns. $z_k(\eta_{rp})$ refers to the total risk premium components (sum of the components due to η_c , η_h and η_d). The estimates are obtained as γ coefficients from the regression :

$$z_{k,t}/z_{k,t}(\eta_i) = \gamma_0 + \gamma D_{FOMC,t} + e_t$$

D_{FOMC} is set to one when it is on a scheduled FOMC meeting day and zero otherwise. The first column of the table reports the class of asset (k): two-year Treasury yield changes (Δy_2), ten-year Treasury yield changes (Δy_{10}), Investment-grade corporate bond yield changes (Δy_{IG}), high-yield corporate bond yield changes (Δy_{HY}), and stock returns (s). In the regression for the second column, the dependent variable is the overall yield changes or stock returns. In the regressions presented from the third to the seventh column, the dependent variables are the historical decompositions of stock returns and yield changes into contributions of structural shocks. The last column separately reports the coefficients for the total risk premium component. Regressions are estimated over the 2000-2023 period, covering 192 scheduled FOMC announcement days. t-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

k	z_k	$z_k(\eta_i)$					
		$z_k(\eta_g)$	$z_k(\eta_m)$	$z_k(\eta_c)$	$z_k(\eta_h)$	$z_k(\eta_d)$	$z_k(\eta_{rp})$
Δy_2	-0.460 (-1.49)	0.070 (0.47)	-0.229 (-1.14)	-0.115** (-2.01)	-0.194 (-1.14)	- -	-0.302* (-1.67)
Δy_{10}	-0.750** (-2.19)	0.037 (0.39)	-0.058 (-0.95)	-0.458** (-2.12)	-0.283 (-1.18)	- -	-0.729** (-2.26)
Δy_{IG}	-0.805*** (-2.65)	0.071 (0.52)	-0.055 (-0.87)	-0.261** (-2.06)	-0.175 (-0.95)	-0.386*** (-2.66)	-0.821*** (-3.09)
Δy_{HY}	-0.332 (-0.68)	0.060 (0.42)	-0.020 (-0.34)	-0.448** (-2.01)	0.451 (1.55)	-0.376 (-1.35)	-0.372 (-0.81)
s	18.107*** (2.58)	1.095 (0.24)	2.701 (1.19)	1.333* (1.90)	-2.537 (-1.03)	15.515*** (3.80)	14.311*** (2.95)

Table 3: FOMC meeting regression (good and bad times)

This table reports the results of regressions of yield changes and stock returns or their decompositions due to η shocks on the dummy variables, reflecting the interactions of FOMC meeting dummy and economy state dummy. z_k represents the overall yield change or stock return. $z_k(\eta_i)$ is the historical decomposition of η_i shock to yield changes or stock returns. $z_k(\eta_{rp})$ refers to the total risk premium components (sum of the components due to η_c , η_h and η_d). The estimates are obtained from the regression:

$$z_{k,t}/z_{k,t}(\eta, t) = \alpha + \beta D_{FOMC,t} + \gamma D_{bad,t} + \delta D_{FOMC,t} * D_{bad,t} + e_t$$

The FOMC meeting dummy (D_{FOMC}) is set to one when it is on a scheduled FOMC meeting day and zero otherwise. The bad time dummy (D_{bad}) is set to one when the Chicago Fed National Activity Index (CFNAI) is below its median of our sample and zero otherwise. The first column of the table reports the class of asset (k): two-year Treasury yield changes (Δy_2), ten-year Treasury yield changes (Δy_{10}), Investment-grade corporate bond yield changes (Δy_{IG}), high-yield corporate bond yield changes (Δy_{HY}), and stock returns (s). In the regression for the second column, the dependent variable is the overall yield changes or stock returns. In the regressions presented from the third to the seventh column, the dependent variables are the historical decompositions of stock returns and yield changes into contributions of structural shocks. The last column separately reports the coefficients for the total risk premium component. Regressions are estimated over the 2000 - 2023 period, covering 192 scheduled FOMC announcement days (100 FOMC announcements in bad times and 92 in good times). t-statistics are reported in parentheses, while p-values of F-test are reported in curly brackets. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

k	z_k	$z_k(\eta_i)$					
		$z_k(\eta_g)$	$z_k(\eta_m)$	$z_k(\eta_c)$	$z_k(\eta_h)$	$z_k(\eta_d)$	$z_k(\eta_{rp})$
Δy_2	α	0.183*	0.070	0.113*	-0.016	0.019	0.000
		(1.78)	(1.40)	(1.69)	(-0.84)	(0.34)	(0.01)
	β	0.115	0.151	-0.108	-0.020	0.088	0.073
		(0.26)	(0.70)	(-0.37)	(-0.24)	(0.36)	(0.28)
	γ	-0.315**	-0.146**	-0.200**	0.044*	-0.017	0.032
		(-2.17)	(-2.09)	(-2.12)	(1.65)	(-0.22)	(0.38)
	δ	-1.118*	-0.154	-0.232	-0.187	-0.550	-0.731**
		(-1.81)	(-0.51)	(-0.58)	(-1.62)	(-1.61)	(-2.02)
	$\beta+\delta$	-1.002**	-0.003	-0.340	-0.207**	-0.462*	-0.659***
		{0.02}	{0.99}	{0.23}	{0.01}	{0.05}	{0.01}
Δy_{10}	$\gamma+\delta$	-1.432**	-0.300	-0.433	-0.142	-0.567*	-0.699**
		{0.02}	{0.30}	{0.27}	{0.20}	{0.09}	{0.05}
	α	0.015	0.043	0.039*	-0.092	0.029	-0.068
		(0.13)	(1.36)	(1.91)	(-1.28)	(0.37)	(-0.63)
	β	0.114	0.088	-0.032	-0.068	0.118	0.058
		(0.23)	(0.65)	(-0.36)	(-0.22)	(0.34)	(0.13)
	γ	0.052	-0.089**	-0.072**	0.233**	-0.027	0.213
		(0.32)	(-2.01)	(-2.49)	(2.29)	(-0.24)	(1.41)
	δ	-1.687**	-0.097	-0.050	-0.767*	-0.782	-1.540**
		(-2.47)	(-0.51)	(-0.41)	(-1.77)	(-1.63)	(-2.38)
Δy_{HY}	$\beta+\delta$	-1.573***	-0.009	-0.082	-0.834***	-0.664**	-1.482***
		{0.00}	{0.94}	{0.34}	{0.01}	{0.05}	{0.00}
	$\gamma+\delta$	-1.636**	-0.186	-0.122	-0.534	-0.809*	-1.327**
		{0.01}	{0.31}	{0.31}	{0.20}	{0.08}	{0.03}

Δy_{IG}	α	-0.018 (-0.18)	0.066 (1.47)	0.041** (1.99)	-0.060 (-1.42)	0.012 (0.20)	-0.078 (-1.62)	-0.125 (-1.42)
	β	0.040 (0.09)	0.140 (0.72)	-0.031 (-0.34)	-0.035 (-0.19)	0.103 (0.39)	-0.138 (-0.67)	-0.069 (-0.18)
	γ	0.123 (0.86)	-0.139** (-2.19)	-0.077*** (-2.60)	0.147** (2.48)	-0.006 (-0.07)	0.197*** (2.91)	0.338*** (2.72)
	δ	-1.652*** (-2.71)	-0.132 (-0.49)	-0.045 (-0.36)	-0.444* (-1.75)	-0.543 (-1.48)	-0.487* (-1.68)	-1.474*** (-2.78)
	$\beta+\delta$	-1.612*** {0.00}	0.008 {0.97}	-0.076 {0.38}	-0.479*** {0.01}	-0.440* {0.09}	-0.625*** {0.00}	-1.543*** {0.00}
	$\gamma+\delta$	-1.529*** {0.01}	-0.271 {0.30}	-0.122 {0.32}	-0.297 {0.23}	-0.549 {0.12}	-0.290 {0.30}	-1.136** {0.03}
	α	-0.263 (-1.63)	0.072 (1.49)	0.047** (2.37)	-0.126* (-1.71)	-0.064 (-0.66)	-0.191** (-2.07)	-0.381** (-2.51)
	β	-0.104 (-0.15)	0.128 (0.61)	-0.022 (-0.26)	-0.048 (-0.15)	-0.089 (-0.21)	-0.073 (-0.18)	-0.210 (-0.32)
	γ	0.558** (2.45)	-0.150** (-2.19)	-0.091*** (-3.27)	0.298*** (2.86)	0.079 (0.58)	0.421*** (3.24)	0.798*** (3.72)
	δ	-0.455 (-0.47)	-0.129 (-0.44)	0.004 (0.04)	-0.785* (-1.76)	1.053* (1.80)	-0.598 (-1.08)	-0.330 (-0.36)
Δy_{HY}	$\beta+\delta$	-0.559 {0.41}	-0.001 {1.00}	-0.017 {0.83}	-0.833*** {0.01}	0.964** {0.02}	-0.671* {0.08}	-0.541 {0.40}
	$\gamma+\delta$	0.104 {0.91}	-0.278 {0.33}	-0.086 {0.45}	-0.487 {0.26}	1.132** {0.05}	-0.177 {0.74}	0.468 {0.60}
	α	2.211 (0.95)	1.929 (1.26)	-1.196 (-1.59)	0.190 (0.82)	0.238 (0.29)	1.049 (0.77)	1.477 (0.92)
	β	13.077 (1.30)	3.560 (0.54)	1.215 (0.37)	0.229 (0.23)	1.404 (0.40)	6.670 (1.14)	8.302 (1.20)
	γ	-6.358* (-1.94)	-3.955* (-1.83)	2.089** (1.97)	-0.524 (-1.60)	-0.199 (-0.17)	-3.771** (-1.97)	-4.493** (-1.98)
	δ	9.929 (0.71)	-4.738 (-0.51)	2.862 (0.63)	2.165 (1.55)	-7.688 (-1.56)	17.329** (2.12)	11.806 (1.22)
	$\beta+\delta$	23.006** {0.02}	-1.178 {0.85}	4.077 {0.20}	2.394** {0.01}	-6.283* {0.07}	23.998*** {0.00}	20.108*** {0.00}
	$\gamma+\delta$	3.571 {0.79}	-8.693 {0.33}	4.952 {0.26}	1.641 {0.23}	-7.887* {0.10}	13.558* {0.09}	7.312 {0.44}
	α	2.211 (0.95)	1.929 (1.26)	-1.196 (-1.59)	0.190 (0.82)	0.238 (0.29)	1.049 (0.77)	1.477 (0.92)
	β	13.077 (1.30)	3.560 (0.54)	1.215 (0.37)	0.229 (0.23)	1.404 (0.40)	6.670 (1.14)	8.302 (1.20)
s	γ	-6.358* (-1.94)	-3.955* (-1.83)	2.089** (1.97)	-0.524 (-1.60)	-0.199 (-0.17)	-3.771** (-1.97)	-4.493** (-1.98)
	δ	9.929 (0.71)	-4.738 (-0.51)	2.862 (0.63)	2.165 (1.55)	-7.688 (-1.56)	17.329** (2.12)	11.806 (1.22)
	$\beta+\delta$	23.006** {0.02}	-1.178 {0.85}	4.077 {0.20}	2.394** {0.01}	-6.283* {0.07}	23.998*** {0.00}	20.108*** {0.00}
	$\gamma+\delta$	3.571 {0.79}	-8.693 {0.33}	4.952 {0.26}	1.641 {0.23}	-7.887* {0.10}	13.558* {0.09}	7.312 {0.44}

Table 4: Asset response on non-farm payroll announcement days

This table reports the average yield changes and stock returns and their decompositions due to η shocks on non-farm payroll (NFP) announcement days, conditional on the type of news and the state of the economy. Good (Bad) NFP news corresponds to a positive (negative) NFP surprise, using actual NFP minus expected NFP. The state of the economy (Good/Bad times) is measured using the two halves of the CFNAI, with the upper half representing good times. z_k represents the overall yield change or stock return. $z_k(\eta_i)$ is the historical decomposition of η_i shock to yield changes or stock returns. $z_k(\eta_{rp})$ refers to the total risk premium components (sum of the components due to η_c , η_h and η_d). The estimates are obtained as γ_1 coefficients and γ_2 coefficients from the regression:

$$z_{k,t}/z_{k,t}(\eta_i) = \gamma_1 D_{BG,t} + \gamma_2 D_{BB,t} + \gamma_3 D_{GG,t} + \gamma_4 D_{GB,t} + e_t$$

The first letter in subscript indicates the type of NFP news; the second letter describes the overall state of the economy (e.g., D_{BG} is a dummy variable for days with bad NFP news coming out in good times). The first column of the table reports the class of asset (k): two-year Treasury yield changes (Δy_2), ten-year Treasury yield changes (Δy_{10}), Investment-grade corporate bond yield changes (Δy_{IG}), high-yield corporate bond yield changes (Δy_{HY}), and stock returns (s). In the regression for the second column, the dependent variable is the overall yield changes or stock returns. In the regressions presented from the third to the seventh column, the dependent variables are the historical decompositions of stock returns and yield changes into contributions of structural shocks. The last column separately reports the coefficients for the total risk premium component. Regressions are estimated over the 2000 - 2023 period, covering 274 NFP announcement days (57 bad NFP news in good times, 77 bad NFP news in bad times, 75 good NFP news in good times and 65 good NFP news in bad times), excluding announcements that fall on a holiday. All numbers are in basis points. t-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

k	z_k	$z_k(\eta_i)$					
		$z_k(\eta_g)$	$z_k(\eta_m)$	$z_k(\eta_c)$	$z_k(\eta_h)$	$z_k(\eta_d)$	$z_k(\eta_{rp})$
Δy_2	γ_1	1.062 (1.63)	0.050 (0.13)	-0.026 (-0.07)	-0.110 (-0.59)	1.139** (2.08)	- (2.15)
	γ_2	-1.280* (-1.79)	-0.799** (-2.03)	0.101 (0.24)	0.027 (0.21)	-0.621 (-1.27)	- (-1.23)
	γ_3	0.824** (2.10)	0.348 (1.62)	0.104 (0.41)	0.162 (1.64)	0.225 (0.80)	- (1.31)
	γ_4	-1.693** (-2.49)	-0.302 (-1.09)	-1.309*** (-2.94)	0.003 (0.02)	-0.069 (-0.22)	- (-0.20)
Δy_{10}	γ_1	1.233 (1.56)	0.028 (0.11)	-0.043 (-0.38)	-0.389 (-0.60)	1.624** (2.14)	- (1.62)
	γ_2	-1.351* (-1.76)	-0.517** (-2.07)	0.026 (0.20)	-0.010 (-0.02)	-0.869 (-1.26)	- (-1.15)
	γ_3	1.147** (2.19)	0.215 (1.58)	0.026 (0.31)	0.589 (1.51)	0.339 (0.85)	- (1.79)
	γ_4	-0.699 (-0.85)	-0.187 (-1.06)	-0.466*** (-3.24)	0.061 (0.11)	-0.083 (-0.19)	- (-0.05)

Δy_{IG}	γ_1	0.843 (1.24)	0.045 (0.13)	-0.051 (-0.46)	-0.230 (-0.61)	1.101* (1.83)	-0.022 (-0.13)	0.849 (1.33)
	γ_2	-0.972* (-1.79)	-0.718** (-2.04)	0.017 (0.13)	-0.034 (-0.12)	-0.678 (-1.30)	0.441* (1.72)	-0.271 (-0.52)
	γ_3	0.875* (1.77)	0.325* (1.68)	0.023 (0.28)	0.330 (1.44)	0.158 (0.53)	0.039 (0.13)	0.527 (1.19)
	γ_4	-1.102* (-1.69)	-0.286 (-1.14)	-0.484*** (-3.30)	0.037 (0.12)	-0.104 (-0.30)	-0.266 (-1.10)	-0.333 (-0.56)
Δy_{HY}	γ_1	-2.581* (-1.67)	0.031 (0.08)	-0.114 (-1.10)	-0.380 (-0.60)	-2.282*** (-2.83)	0.163 (0.51)	-2.499* (-1.94)
	γ_2	0.909 (0.73)	-0.815** (-2.18)	-0.014 (-0.11)	-0.150 (-0.29)	0.939 (1.14)	0.949* (1.80)	1.739 (1.34)
	γ_3	-0.110 (-0.16)	0.354* (1.69)	0.004 (0.04)	0.532 (1.30)	-0.708 (-1.43)	-0.292 (-0.55)	-0.468 (-0.63)
	γ_4	-1.570* (-1.70)	-0.325 (-1.18)	-0.539*** (-3.62)	0.091 (0.17)	-0.042 (-0.08)	-0.755* (-1.78)	-0.706 (-0.82)
s	γ_1	22.381** (2.09)	1.079 (0.09)	-0.199 (-0.05)	1.387 (0.60)	15.866** (1.99)	4.247 (0.82)	21.501** (2.02)
	γ_2	-44.471** (-2.24)	-25.973** (-2.11)	-1.143 (-0.25)	-0.283 (-0.19)	-8.764 (-1.27)	-8.308 (-1.13)	-17.355 (-1.43)
	γ_3	1.879 (0.16)	9.888 (1.49)	-1.240 (-0.44)	-1.920 (-1.61)	2.733 (0.69)	-7.581 (-0.88)	-6.768 (-0.78)
	γ_4	5.233 (0.44)	-8.582 (-0.99)	13.583*** (2.79)	0.027 (0.02)	-1.480 (-0.33)	1.685 (0.22)	0.233 (0.02)

Table 5: Comovement decomposition

This table reports the average correlations among negative yield changes and stock returns and their decompositions into the contribution of structural economic shocks over various time periods. The overall correlation (ρ) between asset price changes z_x and z_y is represented as a sum of decompositions due to individual structural shocks: $\rho = \rho_g + \rho_m + \rho_c + \rho_h + \rho_d$. The correlation component is constructed as the covariance between the decompositions of asset price changes divided by the standard deviation of the overall asset price changes (e.g., $\rho_g = Cov(z_x(\eta_g), z_y(\eta_g))/(\sigma_{z_x}\sigma_{z_y})$). ρ_{rp} refers to the total risk premium correlation component (sum of the components due to η_c , η_h , and η_d). The analysis covers the full sample period from August 2000 to December 2023, with specific examination of two recent recessions: the Financial Crisis (December 2007–June 2009) and the COVID-19 pandemic (February–April 2020). t-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level.

(z_x, z_y)	Sample	ρ	ρ_g	ρ_m	ρ_c	ρ_h	ρ_d	ρ_{rp}
(y_{10}, y_{IG})	Full	0.843***	0.122***	0.037***	0.263***	0.417***	-	0.683***
		(119.52)	(9.41)	(2.84)	(20.82)	(35.04)	-	(71.44)
	GFC	0.769***	0.181***	0.043	0.205***	0.337***	-	0.538***
		(23.84)	(3.65)	(0.86)	(4.15)	(7.11)	-	(12.66)
	Covid-19	0.360***	0.040	0.049	0.148	0.087	-	0.288**
		(2.96)	(0.31)	(0.38)	(1.17)	(0.68)	-	(2.35)
(y_{10}, y_{HY})	Full	-0.003	0.083***	0.021	0.285***	-0.400***	-	-0.107***
		(-0.26)	(6.33)	(1.59)	(22.69)	(-33.28)	-	(-8.24)
	GFC	-0.051	0.087*	0.013	0.220***	-0.380***	-	-0.161***
		(-1.01)	(1.72)	(0.25)	(4.48)	(-8.15)	-	(-3.23)
	Covid-19	-0.174	0.023	0.018	0.100	-0.358***	-	-0.247**
		(-1.36)	(0.18)	(0.14)	(0.79)	(-2.99)	-	(-1.99)
(y_{10}, s)	Full	-0.307***	-0.181***	0.057***	0.061***	-0.245***	-	-0.186***
		(-24.66)	(-14.03)	(4.32)	(4.65)	(-19.28)	-	(-14.48)
	GFC	-0.372***	-0.340***	0.038	0.101**	-0.172***	-	-0.075
		(-7.94)	(-7.17)	(0.75)	(2.01)	(-3.47)	-	(-1.49)
	Covid-19	-0.516***	-0.052	-0.031	-0.080	-0.328***	-	-0.488***
		(-4.62)	(-0.40)	(-0.24)	(-0.63)	(-2.71)	-	(-4.37)
(y_{IG}, y_{HY})	Full	0.276***	0.132***	0.024*	0.189***	-0.322***	0.254***	0.119***
		(21.92)	(10.20)	(1.84)	(14.70)	(-25.93)	(20.09)	(9.15)
	GFC	0.249***	0.101**	0.009	0.126**	-0.289***	0.307***	0.118**
		(5.09)	(2.02)	(0.18)	(2.52)	(-6.00)	(6.41)	(2.36)
	Covid-19	0.720***	0.061	0.016	0.142	-0.060	0.568***	0.745***
		(7.97)	(0.48)	(0.13)	(1.12)	(-0.47)	(5.39)	(8.73)
(y_{IG}, s)	Full	-0.146***	-0.288***	0.064***	0.039***	-0.211***	0.249***	0.077***
		(-11.30)	(-22.95)	(4.93)	(3.02)	(-16.45)	(19.67)	(5.92)
	GFC	-0.253***	-0.385***	0.028	0.055	-0.149***	0.200***	0.100**
		(-5.18)	(-8.28)	(0.55)	(1.10)	(-2.99)	(4.06)	(2.00)
	Covid-19	0.231*	-0.051	0.007	-0.001	-0.049	0.336***	0.303**
		(1.82)	(-0.40)	(0.05)	(-0.01)	(-0.38)	(2.78)	(2.48)
(y_{HY}, s)	Full	0.299***	-0.196***	0.034**	0.041***	0.194***	0.229***	0.463***
		(23.94)	(-15.25)	(2.57)	(3.13)	(15.10)	(17.93)	(39.87)
	GFC	0.178***	-0.187***	0.007	0.061	0.165***	0.123**	0.340***
		(3.58)	(-3.79)	(0.13)	(1.21)	(3.32)	(2.46)	(7.17)
	Covid-19	0.562***	-0.015	0.023	0.094	0.203	0.251**	0.624***
		(5.22)	(-0.11)	(0.18)	(0.74)	(1.62)	(2.03)	(6.24)

Table 6: Impact of economic shocks on the monetary policy surprises

This table reports the results of regressions of monetary policy surprises on the economic shocks (η) over the FOMC announcement periods. The dependent variables are the target and path monetary policy surprise factors from Swanson (2021). The sample period spans from August 2000 to June 2019. The regressions in Panel A use all FOMC meetings (scheduled and unscheduled), while those in Panel B only use scheduled meetings. Regression coefficients are expressed in standard deviation units. The last column reports the adjusted R-squared. t-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level.

	η_g	η_m	η_c	η_h	η_d	R^2
Panel A: All FOMC meetings						
Target	-0.021 (-0.37)	0.199*** (4.09)	-0.106* (-1.86)	0.081 (1.45)	0.071 (1.10)	0.139
Path	0.141* (1.77)	0.184*** (2.76)	0.222*** (2.83)	-0.148* (-1.94)	0.211** (2.37)	0.108
Panel B: Scheduled FOMC meetings						
Target	0.003 (0.01)	0.110*** (3.10)	-0.038 (-0.96)	0.060 (1.60)	0.028 (0.60)	0.085
Path	0.033 (0.41)	0.282*** (3.87)	0.115 (1.42)	-0.191** (-2.50)	0.115 (1.23)	0.108

Table 7: Impact of economic shocks on the asset risk premium

This table reports the results of regressions of innovations in the bond and equity risk premium on η shocks. Treasury risk premium (RP_T) is proxied as ten-year treasury yields minus the risk-free rates (three-month treasury bill rates). Investment-grade corporate bond risk premium (RP_{IG}) and high-yield corporate bond risk premium (RP_{HY}) are proxied as investment-grade corporate yields and high-yield corporate yields minus the risk-free rates. Equity risk premium (ΔRP_S) is the daily forward equity premium from [Martin \(2017\)](#). Innovations to the risk premium proxies (ΔRP) are computed as differential of the risk premium series. The last column reports the adjusted R-squared. t-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level.

	η_g	η_m	η_c	η_h	η_d	R^2
ΔRP_T	0.934***	-0.416***	4.033***	-3.335***	-	0.602
	(16.42)	(-7.31)	(70.86)	(-58.61)	-	
	-	-	4.033***	-3.335***	-	0.581
	-	-	(68.99)	(-57.06)	-	
ΔRP_{IG}	1.646***	-0.401***	2.463***	-2.302***	2.758***	0.522
	(28.09)	(-6.85)	(42.03)	(-39.28)	(47.08)	
	-	-	2.463***	-2.302***	2.758***	0.453
	-	-	(39.31)	(-36.74)	(44.03)	
ΔRP_{HY}	1.814***	-0.570***	4.042***	5.702***	3.963***	0.676
	(24.22)	(-7.61)	(53.96)	(76.12)	(52.91)	
	-	-	4.042***	5.702***	3.963***	0.640
	-	-	(51.21)	(72.24)	(50.22)	
ΔRP_S	-12.695***	7.411***	2.630***	9.890***	15.100***	0.642
	(-43.36)	(22.79)	(7.98)	(31.59)	(44.37)	
	-	-	2.183***	9.843***	14.885***	0.339
	-	-	(4.87)	(23.20)	(32.32)	

Internet Appendix

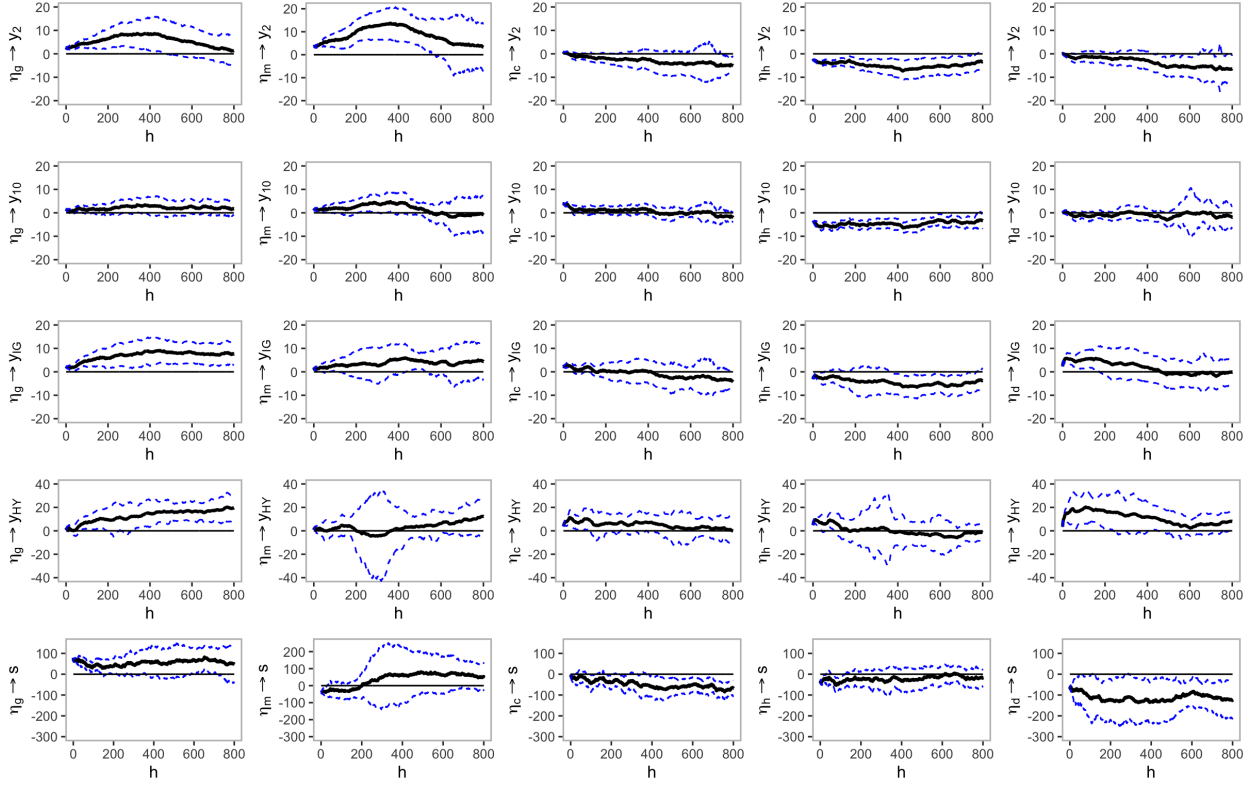


Figure A1: Impulse response functions. The figure presents responses of yield changes and stock returns to identified shocks up to a maximum horizon of about three years (800 business days). Shocks correspond to the MT solution and are measured in standard deviation units. Yield changes and stock returns are in basis points. The solid line denotes the coefficients $\beta_h^{j,i}$ from the regression $Y_{t+h}^j - Y_{t-1}^j = \alpha_h + \beta_h^{j,i} \eta_t + \kappa_{t-1,t+h}$. Horizon h is in business days. The dashed lines mark 95% confidence intervals calculated with Newey-West adjustment using $h+1$ lags. The sample period is 2000–2023.

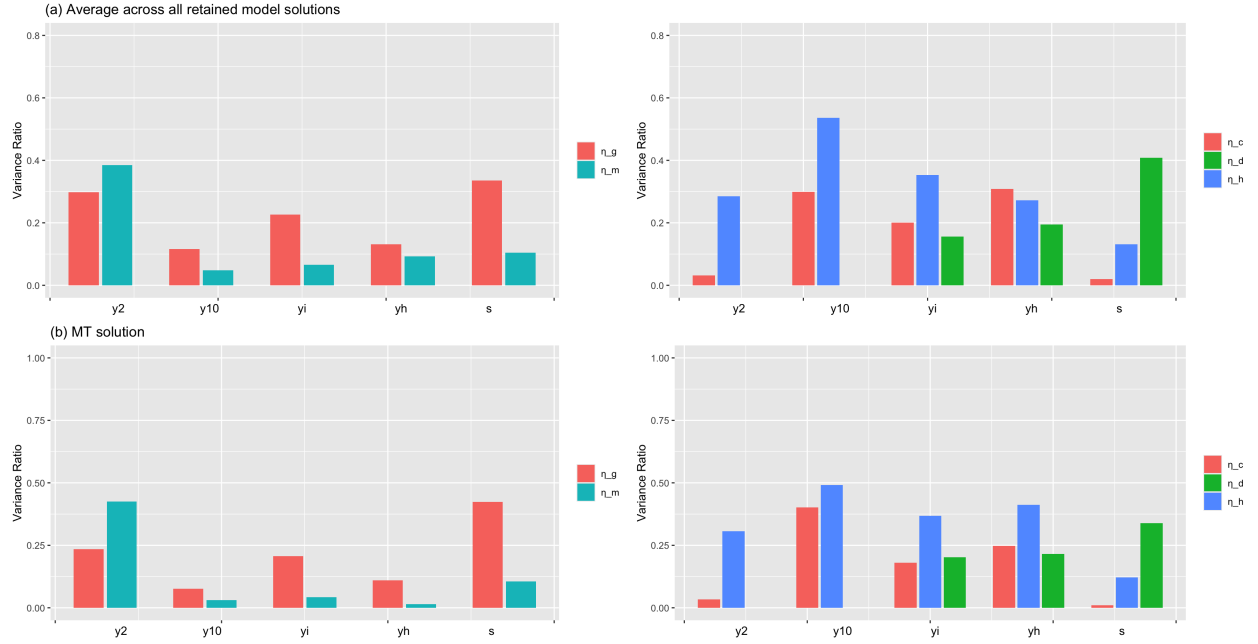


Figure A2: Variance ratios. The figure presents variance decompositions of innovations in daily Treasury yield changes with maturities of two and ten years, investment-grade and high-yield corporate yield changes, and stock returns into structural shocks. The bars show the fraction of variance explained by each shock on average across all retained model solutions in panel A, while the MT solution in panel B. Variance ratios across shocks sum to unity by construction.

Table A1: FOMC dummy regression

This table reports the results of the regression of absolute values of identified structural shocks ($|\eta|$) on the FOMC meeting dummy (D_{FOMC}). The estimates are obtained as γ_0 and γ_1 from the regression:

$$|\eta_t| = \gamma_0 + \gamma_1 D_{FOMC,t} + e_t$$

D_{FOMC} is set to one when it is on a scheduled FOMC meeting day. Shocks are expressed in units of standard deviations. Regressions are estimated over the 2000-2023 period, covering 196 scheduled FOMC announcement days. t-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level.

	$ \eta_g $	$ \eta_m $	$ \eta_c $	$ \eta_h $	$ \eta_d $
γ_1	-0.025 (-0.58)	0.226*** (5.20)	0.047 (1.12)	0.067 (1.58)	0.079* (1.72)
γ_0	0.671*** (67.20)	0.639*** (62.78)	0.684*** (70.00)	0.666*** (66.69)	0.595*** (55.25)
N	5831	5831	5831	5831	5831

Table A2: Scenario-Based Mapping of Regression Specification

This table summarizes the logical structure of the regression specification: $z_{k,t} = \alpha + \beta D_{FOMC,t} + \gamma D_{bad,t} + \delta D_{FOMC,t} \cdot D_{bad,t} + e_t$. It decomposes expected asset price responses across FOMC and non-FOMC days under bad and good economic states, and isolates the marginal FOMC effect and business cycle differentials.

Scenario	FOMC Days	Non-FOMC Days	FOMC Effect
Bad times (B)	$\alpha + \beta + \gamma + \delta$	$\alpha + \gamma$	$\beta + \delta$
Good times (G)	$\alpha + \beta$	α	β
Business Cycle Effect	$\gamma + \delta$	γ	—

This table outlines how asset prices respond various possible combinations of FOMC announcement days and macroeconomic conditions (good vs. bad times). Each coefficient in the regression has a distinct economic meaning. The intercept term α captures the baseline level effect, representing the average asset price response on non-FOMC days during good times. The coefficient β measures the incremental effect of FOMC announcements relative to non-FOMC days in good times, isolating the marginal influence of monetary policy under favorable conditions. The coefficient γ captures the incremental effect of macroeconomic deterioration, reflecting the average change in asset prices between bad and good times on non-FOMC days. Finally, the interaction term δ measures the incremental effect of FOMC announcements in bad times relative to the incremental effect of FOMC announcements in good times, allowing us to quantify how the marginal effect of policy changes with the business cycle.