Macroeconomic News and Stock–Bond Comovement

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Abstract

Stock returns and changes in bond yields are projected on survey-based news about current and future output growth and inflation. The projections generate macro-spanned stock returns and yield changes, as well as non-macro residuals. The late-1990s change in the sign of covariances between stock returns and changes in bond yields is entirely attributable to covariances between non-macro residuals. By contrast, covariances between macro-spanned components are stable, largely positive, and unrelated to news about inflation. Asset-pricing models that explain the late-1990s sign change through changing inflation dynamics require much more news about inflation than the data support.
1 Introduction

The comovement between stock and nominal bond yields varies widely over time, occasionally switching sign. Figure 1 illustrates patterns first identified by Li (2002) and Fleming, Kirby, and Ostdiek (2003). The figure displays rolling two-month sample correlations between daily aggregate stock returns and contemporaneous changes in Treasury yields. Sample correlations are close to zero in the early 1960s. Stock returns and bond yields move in opposite directions from the late 1960s through the late 1990s. After an abrupt sign change around 1997, yields and stock returns move together throughout much of the 21st century. This time-variation in daily comovement also holds for monthly, quarterly, and annual horizons.

An active theoretical literature beginning with Hasseltoft (2009) attempts to explain the dynamics of this comovement, especially the sign change associate with the sharp break. Almost all of these theories emphasize how time-varying dynamics of inflation and output affect the conditional comovement between stock and bond returns. In this research I take a high-level perspective to argue that these theories have little empirical support.

Much of this literature emphasizes the role of expected inflation. Expected inflation was countercyclical during the 1960s through the early 1990s and procyclical after this period. In Burkhardt and Hasseltoft (2012), David and Veronesi (2013), Song (2017), and Campbell, Pflueger, and Viceira (2020), this change in regime drives the large swings in correlations observed in Figure 1, including the change in sign.

Other research emphasizes the role of real rates. Campbell, Shiller, and Viceira (2009), Campbell, Sunderam, and Viceira (2017), and Liu (2020) all observe that the conditional comovement between stock returns and long-term inflation-indexed yields is roughly similar to the conditional comovement between stock returns and long-term nominal yields. Campbell et al. (2009) note that when the stochastic discount factor is connected to aggregate consumption dynamics, time-variation in the autocorrelation function of aggregate consumption produces time-variation in conditional covariances between real yields and stock returns. Jones and Pyun (2021) and Liu (2020) use this intuition to explain time-varying comovement between yields and stock returns, in endowment and production economies respectively.

I investigate whether the responses of stock returns and bond yields to macroeconomic news have changed enough over time to explain the break in Figure 1 in the late 1990s. I study the period 1969 through 2019, where the ending date is chosen to exclude the pandemic.
For this exercise, macro news is inferred from quarterly revisions in survey forecasts of future real output and inflation. Stock returns and changes in bond yields are regressed on this news, producing macro news-linked components and residual components.

The data do not support the conclusion that the break in the late 1990s is driven by changing responses to macro news. For example, during the 1997 through 2019 period, macro news-linked components of quarterly stock returns and quarterly changes in one-year bond yields (nominal and real) are positively correlated. This sign is not surprising, given that Figure 1 displays the same sign for the 1997 through 2019 period. However, during the 1969 through 1996 period, macro news-linked components of stock returns and changes in these one-year bond yields are also positively correlated. By contrast, the correlation between residual (non-macro news) components of stock returns and changes in bond yields is negative and large in the early part of the sample, and positive since the late 1990s. Results for a long-term nominal yield are similar.

These results prompt an obvious question. Why does earlier research argue that various asset-pricing models explain the observed change in stock–bond comovement over time? I explore this question for a few inflation-centric models in the literature. For this exercise I follow the approach in Duffee (2018), who documents that standard deviations of innovations in expected inflation are small relative to standard deviations of innovations in bond yields. Because these standard deviations are so small, changes in covariances between stock returns and news about expected inflation contribute relatively little to changes in covariances between stock returns and nominal bond yields. Research that finds an important role for inflation dynamics assumes that news about expected inflation has properties wildly different from what we observe.

The next section discusses the factor model framework I use to study stock–bond comovement. It also describes the data. Section 3 presents results for the factor model. Section 4 discusses the literature that attempts to explain time-varying comovement with time-varying inflation dynamics. Section 5 concludes.

2 Factor Models

Denote period-\(t\) yields on \(n\)-period zero-coupon real and nominal bonds as \(r_t^{(n)}\) and \(y_t^{(n)}\) respectively. Denote innovations to these yields (i.e., realizations less period \(t-1\) expectations)
with tildes, $\tilde{r}_{t}^{(n)}$ and $\tilde{y}_{t}^{(n)}$. Denote the period-$t$ innovation to the excess stock market return as $\tilde{x}r_{m,t}$. These innovations are driven, at least in part, by innovations to a macroeconomic state vector,

$$\epsilon_t \equiv X_t - E_{t-1}(X_t), \quad E_{t-1}(\epsilon_t\epsilon_t') = \Omega(X_{t-1}). \quad (1)$$

Innovations to stock returns and bond yields are conditionally linear functions of the macroeconomic state innovations and a residual (non-state) component,

$$\tilde{x}r_{m,t} = \beta_m(X_{t-1})'\epsilon_t + \psi_{m,t}, \quad (2)$$
$$\tilde{r}_{t}^{(n)} = \beta_r^{(n)}(X_{t-1})'\epsilon_t + \psi_{r,t}^{(n)}. \quad (3)$$
$$\tilde{y}_{t}^{(n)} = \beta_y^{(n)}(X_{t-1})'\epsilon_t + \psi_{y,t}^{(n)}. \quad (4)$$

Aside from linearity, these equations are fairly general. For example, one element of the vector of macroeconomic innovations might affect only the stock market, while another element might affect only nominal yields. In addition, time-variation in the beta vectors might depend only on a subset of the elements of the state vector.

Given (2), (3), and (4), the conditional covariance between the stock market return and a bond’s yield is the sum of a factor-innovation component and a residual component. For example, the conditional covariance between the stock market return and the yield on a real bond is

$$\text{Cov}_{t-1}(\tilde{x}r_{m,t}, \tilde{r}_{t}^{(n)}) = \beta_m(X_{t-1})'\Omega(X_{t-1})\beta_r^{(n)}(X_{t-1}) + \text{Cov}_{t-1}(\psi_{m,t}, \psi_{r,t}^{(n)}). \quad (5)$$

Similar functional forms express other conditional covariances and variances.

From a formal perspective, two channels create variation in the factor-driven component of the conditional covariance (5). First, the conditional covariance matrix of macroeconomic shocks can vary, changing the relative importance of different fundamental shocks. For example, assume that one element of the macroeconomic innovation vector drives stock returns and bond yields in opposite directions, while another drives them in the same direction. High conditional volatility of the first (second) element induces a negative (positive) conditional correlation between stock returns and yields. Second, sensitivities of stock returns and/or bond yields to macroeconomic innovations can vary over time.
From an economic perspective, tight connections link these two channels. The information contained in a macroeconomic innovation changes when conditional covariances among these innovations change. If the information content changes, the betas in (2), (3), and (4) will also change because agents will change how they interpret macroeconomic innovations.

2.1 Baele, Bekaert, and Inghelbrecht (2010)

Baele, Bekaert, and Inghelbrecht (2010), hereafter BBI, implement empirically a version of this factor-based approach in an attempt to understand why stock–bond comovement has varied widely in the U.S. since the 1960s. They conclude that although the model has explanatory power for conditional variances, “...the factor model primarily fails in fitting covariances.” Here I discuss features of BBI’s factor model that help determine the structure of the factor model described in Section 2.2.

Their factor model explains innovations to stock returns and a single long-term nominal bond yield. They model bond returns rather than innovations in yields as in (4). That choice is unimportant. The residual components in (2) and (4) are assumed iid,

\[
\begin{pmatrix} \psi_{m,t} \\ \psi_{y,t}^{(n)} \end{pmatrix} \sim N \left( \begin{pmatrix} \sigma_{m}^{2} & 0 \\ 0 & \sigma_{n}^{2} \end{pmatrix} \right).
\]

Since the residuals are homoskedastic, time-varying conditional second moments of stock and bond returns are produced exclusively by variation in the loadings on factor innovations (the \( \beta \) vectors) and/or variation in the conditional covariance matrix of the innovations.

Forward-looking agents price stocks and bonds, thus the prices respond to news about current and future economic conditions. BBI choose observable factors that capture current macroeconomic conditions. They assume that investors’ information about future macroeconomic conditions is subsumed in the current state of the economy. Similarly, they include factors for current asset-market liquidity rather than forecasts of future liquidity. The only explicitly forward-looking factors are the variance risk premium and estimates of macroeconomic uncertainty from surveys of forecasters.\(^1\)

BBI do not observe directly the innovations in (1). Instead, they produce fitted inno-

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\(^1\)They use survey forecasts of output and inflation, but only as one-period-ahead forecasts on the right-hand sides of New Keynesian dynamic equations.
vations with estimated dynamic models. They explore a variety of a priori restrictions on vector autoregressions with dynamics (including the dynamics of the conditional covariance matrix of innovations) that depend on nine regime-switching state variables. The chosen functional form produces fitted residuals that pass various statistical specification tests.

BBI explore alternative functional forms for the beta vectors in (2) and (4). They explain that a version of their model with constant betas cannot generate sign changes in the conditional covariance between stock and bond returns. With constant betas, stock and bond returns share significant exposure to only one of their chosen factors. Thus, the sign of the conditional covariance between stock and bond returns is the sign of the product of their respective (fixed) exposures.

A somewhat more successful version of this model assumes that betas vary with the variance risk premium. This allows the beta of stocks with respect to short-term interest rates to vary from positive to negative over time. However, the model-implied variation in conditional covariances does not match well with the observed variation. The variance risk premium has a strong business cycle component, while (as Figure 1 shows) the dynamics of the conditional covariance are more like a regime shift.

2.2 A forward-looking macroeconomic model

I construct a factor model in which the observed factors are forecasts of current and future real output and inflation. The factor innovations are observed directly rather than inferred from an estimated vector autoregression. The conditional covariance matrix of the factor innovations in (1) and the beta vectors in (2), (3), and (4) are functions only of a dummy variable that allows these parameters to change in the late 1990s.

The model’s simple structure responds to the lessons of BBI. They build a highly parameterized model of factor dynamics that relies critically on the hypothesis that the estimated dynamics match those used by investors in pricing stocks and bonds. Here there is no model of factor dynamics other than the one-time change in the conditional covariance matrix of factor innovations. This assumption of a one-time change is much less ambitious than the dynamic structure in BBI. I avoid attempting to match higher-frequency variations in conditional covariances and betas in an effort to capture a lower-frequency variation.
2.2.1 Macroeconomic factors

The model’s macroeconomic innovations are principal components of revisions in quarterly output and inflation forecasts from the Survey of Professional Forecasters (SPF). Forecasts reported by the SPF are made in the middle of the quarter, just after NIPA announces preliminary estimates for the previous quarter. The maintained hypothesis is that forecasters in the middle of quarter $t$ use all available information to predict output growth and inflation at $t + i$. Thus changes from $t − 1$ to $t$ in consensus forecasts of output growth and inflation for quarter $t + i$ summarize the news arriving from mid-quarter $t − 1$ to mid-quarter $t$ about the macroeconomic state during quarter $t + i$. The Appendix contains details about the construction of these forecast innovations.

Forecast innovations at $t$ are available for quarters $t − 1$ through $t + 3$. I compress the five GDP forecast innovations into three principal components of GDP news. Separately, I compress the five inflation forecast innovations into three principal components of inflation news. These six quarterly time series summarize fundamental macroeconomic innovations. The first available observation is 1969Q1. I use data through 2019Q4 to avoid the pandemic era. Five observations in the first few years are dropped owing to missing observations of three-quarter-ahead forecast innovations. Section 3.1 discusses properties of these innovations.

Conspicuously missing from this measure of macroeconomic innovations is the innovation in the Fed funds rate or a similar short-term interest rate. Macroeconomic models usually treat the Fed funds rate as a target under the control of the central bank, thus any innovation in the Fed funds rate is by construction also a macroeconomic innovation. In such models, any innovation in the Fed funds rate is accompanied by innovations in either expected output growth, expected inflation, or both. Within the context of these models, innovations in the Fed funds rate are redundant as long as there are no more than six important sources of macroeconomic uncertainty.

Empirically, news about expected future output growth and inflation do not span innovations in Fed funds. Labeling such unspanned news as “macroeconomic innovations” broadens the meaning of this label more than I prefer. Imagine, say, that investors suddenly grow more fearful of stocks, leading to a selloff in stock prices that the Fed attempts to soften by cutting the Fed funds rate, raising bond prices. Professional forecasters might treat this event as unimportant for macroeconomic growth and inflation, leaving their forecasts un-
changed. Including Fed fund innovations in the macroeconomic innovation vector treats this event as a “macroeconomic innovation.” The factor model here treats it as an unexplained residual.

2.2.2 Bond yields and stock returns

Like BBI, I use the factor model to explain joint variation in stock returns and a long-term nominal bond yield. Long-term nominal bonds are affected by news about real rates, inflation, and risk premia. To help disentangle these types of news, I also include shorter-maturity real and nominal yields.

Stock returns and changes in bond yields must match the mid-quarter timing of SPF surveys. The aggregate stock return in quarter $t$ is the simple return from the middle of the second month in quarter $t - 1$ to the middle of the second month in quarter $t$. The excess stock return for quarter $t$ is this aggregate stock return less the return to a three-month Treasury bill purchased in the middle of quarter $t - 1$. Mid-quarter yields on one-year and seven-year nominal zero-coupon Treasury bonds are from Gurkaynak, Sack, and Wright (2007). Gurkaynak et al. (2007) recommend using maturities no longer than seven years for part of the sample period examined here.

Prompted by the work of Campbell et al. (2009), Campbell et al. (2017), and Liu (2020), I also examine the relation between a one-year real yield and the macroeconomic innovations. There are no liquid markets for short-term inflation-indexed government debt. Thus beginning with Pennacchi (1991), researchers studying real-rate behavior typically use survey forecasts of inflation to construct ex-ante real yields. I measure the ex-ante one-year real yield in quarter $t$ as the one-year nominal Treasury yield less the contemporaneous consensus forecast of inflation over the next four quarters. Details about this construction are in the online Appendix.

This methodology presumes that consensus survey forecasts correspond to subjective forecasts of marginal investors. We do not observe forecasts of marginal investors. However, substantial research supports the view that consensus forecasts are, from an econometric perspective, as accurate as any other type of forecast. Duffee (2018) discusses the evidence of Ang, Bekaert, and Wei (2007), Faust and Wright (2009), Croushore (2010), Chernov and Mueller (2012), and Faust and Wright (2013). An alternative view, advocated by Coibion and Gorodnichenko (2012), is that consensus inflation forecasts are sticky owing to some
inattentive respondents. The online Appendix to Duffee (2018) argues their results are more likely attributable to specific unforecastable events that produce in-sample patterns that look like stickiness.

2.2.3 Model structure

The factor model expresses excess stock market returns and changes in bond yields as functions of the macroeconomic innovations. A dummy variable allows for the model parameters to change at the end of 1996. The dummy is

\[ D_t = \begin{cases} 
0, & 1969Q1 \leq t < 1997Q1; \\
1, & 1997Q1 \leq t < 2020Q1.
\end{cases} \]  

(7)

Bansal, Connolly, and Stivers (2014), based on evidence such as Figure 1, use the same break point to study changes in stock–bond dynamics. Campbell et al. (2020) illustrate an alternative approach to determining a break point. Motivated by the view stock–bond dynamics should be driven by macroeconomic dynamics, they search for a plausible breakpoint in the latter. They split their sample in 2001. Much research uses regime-switching Markov models to identify joint breaks in stock–bond dynamics, macroeconomic dynamics, and monetary policy, such as BBI, Burkhardt and Hasseltoft (2012), and Song (2017). This earlier research is more ambitious than my big-picture approach.

The left sides of equations (2), (3), and (4) are innovations in stock returns and bond yields. We do not observe directly these innovations. I instead use demeaned stock returns and changes in bond yields. The vector that proxies for asset innovations is

\[ a_t \equiv \left( x_{m,t} - \bar{x}_{m} \right) \Delta r_t^{(1yr)} \Delta y_t^{(1yr)} \Delta y_t^{(7yr)} \]  

(8)

For stock returns and long-term yields, these proxies are close to innovations. Predictable variation in quarterly excess stock returns is swamped by the unpredictable variation. The best in-sample forecasts of one-quarter-ahead stock returns have \( R^2 \)'s of only around 10\%, as in Lettau and Ludvigson (2001). The out-of-sample instability of these forecasts documented by Goyal and Welch (2008) strongly suggests that true predictability is substantially smaller. Much research following Duffee (2002) shows the difficulty of beating random-walk forecasts.
of long-term nominal yields.

Quarterly changes in shorter-term yields contain predictable components. However, these components do not contaminate the covariances of interest. I defer the explanation until after presenting the equations of the factor model.

The factor model is

\[ a_t = (B_E (1 - D_t) + B_L D_t) \epsilon_{t+1} + \psi_t, \]  
(9)

\[ \psi_t = \left( \begin{array}{cccc} \psi_{m,t} & \psi_{r,t} & \psi_{y,t} & \psi_{y,t} \\ \end{array} \right)'. \]  
(10)

The length-six vector \( \epsilon_{t+1} \) contains macroeconomic innovations. The \((4 \times 6)\) matrices \( B_i \) are the loadings on the macroeconomic news, subscripted “E” for the early period and “L” for the late period.

Equation (9) is not a structural or quasi-structural description of how macroeconomic forces affect interest rates and stock returns. The idea of (9) is that any macroeconomic shock that moves stock and bond prices (the left sides of these equations) also affect current and/or expected future output and inflation (the right sides).

The conditional covariances of the macroeconomic innovations and the non-macroeconomic residuals are

\[ E_{t-1} (\epsilon_t \epsilon_t') = \Omega_E (1 - D_t) + \Omega_L D_t, \]  
(11)

\[ E_{t-1} (\psi_t \psi_t') = \Sigma_E (1 - D_t) + \Sigma_L D_t, \]  
(12)

\[ E_{t-1} (\epsilon_t \psi_t') = 0. \]  
(13)

The conditional covariance matrix of stock returns and changes in bond yields is

\[ E_{t-1} (a_t a_t') = \left( B_E \Omega_E B_E' + \Sigma_E \right) (1 - D_t) + \left( B_L \Omega_L B_L' + \Sigma_L \right) D_t. \]  
(14)

The labels in (14) simplify the presentation of results in the next section.

I now return to discussing the proxies for asset innovations. The use of changes in short-term yields rather than innovations in short-term yields does not contaminate the covariances of interest. Conditional means at \( t - 1 \) of changes in short-term yields at \( t \) are known by agents at \( t - 1 \). They are orthogonal to macroeconomic news at \( t \). Therefore these conditional means appear in the residual of (9) rather than in the loadings on the macroeconomic news,
and do not affect estimates of the loadings on this news. They affect (14) only by affecting the $(2 \times 2)$ submatrix of (12) containing variances of the one-year yields and their covariance.

3 Empirical Results

This section discusses how I estimate Section 2.2’s model and interprets the estimation results.

3.1 Preliminaries

Modeling a parameter break at the end of 1996 makes sense only if there is clear evidence that second moments prior to the break differ from those after the break. Table 1 uses the quarterly data described in Section 2.2.2 to confirm that stock returns and changes in bond yields are negatively correlated in the sample ending in 1996. They are positively correlated in the sample beginning with 1997. Table 2 uses Generalized Methods of Moments (GMM) tests to evaluate the hypothesis that covariance between stock returns and changes in bond yields are constant across the two periods. The test is described in detail in the online Appendix. For each bond yield the test easily rejects the hypothesis of constant covariances.

An important message in Table 2 that the change in stock—bond covariance is approximately the same for all the bonds. Therefore Occam’s razor points us towards explanations based on dynamics of short-term real rates, rather than dynamics of inflation and/or risk premia. The factor model is not sufficiently rich to disentangle these possibilities. That said, none of the results discussed in the remainder of this paper suggest that inflation plays a significant role in stock–bond comovement.

Table 3 summarizes properties of the macroeconomic innovations. Panel A shows that most of the news that arrives between the middle of quarter $t - 1$ and the middle of quarter $t$ is about what happened during quarter $t - 1$. Forecasters at $t - 1$ are guessing what is happening during the quarter, while forecasters at $t$ know the preliminary NIPA estimates of GDP and inflation. Across both time periods and both macroeconomic variables, standard deviations of forecast innovations at $t$ for quarter $t - 1$ are more than 2.5 times the standard deviations of forecast innovations at $t$ for quarter $t$.

period reveals two patterns. First, both output news and inflation news are more volatile in the earlier period. Second, in the earlier period there is relatively more news about the future. For GDP growth, the standard deviation of $t-1$ news in the earlier period is about 1.1 times the corresponding standard deviation for the later period. For inflation, the ratio is about 1.6. At forecast horizons $t+2$ and $t+3$, these ratios are around 2.5.

Principal components conveniently summarize joint variation of forecast innovations for different horizons. I decompose separately the covariance matrices of forecast innovations for output growth and inflation for the full sample 1969 through 2019. Figure 2 displays the loadings of the principal components at different horizons. Panel B of Table 3 reports the relative variances of each principal component. For both GDP growth and inflation, the first principal component accounts for more than 3/4 of the overall variation of the forecast innovations, while the first three account for about 96%.

The evidence of Panel B and Figure 2 motivates my choice to summarize macroeconomic news using only the first three principal components of both variables. Discarding the higher principal components reduces the dimension of the factor model while reducing substantially the risk of overfitting the variation of stock returns and bond yields with macro news. This is not a hypothetical issue. In the earlier sample, the covariation of stock returns with the fifth PC is greater (in absolute terms) than its covariation with the third and fourth PCs. Given the negligible contribution of the fifth PC to macroeconomic news, this sample covariation is unlikely to reflect a true macroeconomic component to stock returns.

Table 4 reports results of regressions of stock returns and changes in bond yields on the six combined principal components of news about output growth and inflation. Across both sample periods, this macroeconomic news explains roughly 1/3 of the variation in bond yields. The low explanatory power of macro news for bond yields is consistent with the macro-finance literature. See, e.g., the handbook discussion of Duffee (2013).

Perhaps more surprising are the low $R^2$s for stock returns. The $R^2$ for excess stock returns is 12 percent in the early period, rising to 34 percent in the late period. Naturally, stock returns are not driven only by news about output and inflation. For example, shocks to risk premia (perhaps owing to volatility shocks) also affect stock returns. The explanatory power in the early sample leads to low precision in estimates of macro-induced covariances between stock returns and bond yields.
3.2 Model estimates

I estimate (9), (11), and (12) with exactly-identified GMM. The moments are the ordinary least-squares (OLS) moments of (9), the outer product moments of the macroeconomic innovations for (11), and the outer product moments of the residuals of (9) for (12). Asymptotic standard errors use one lag of moving average residuals.

Table 5 displays the main results. It reports, for each bond, the macro news/non-macro news decomposition of the covariance between stock returns and changes in the bond’s yield. To simplify the language that follows, the terms “macro news covariances” refers to elements two through four of the first columns of the “macro” matrices in (14). These are covariances between stock returns and changes in bond yields produced by the assets’ loadings on the macroeconomic news. The term “non-macro news covariances” refers elements two through four of the first columns of the “non-macro” matrices in (14), produced by the assets’ residuals from the projections on macro news in (9).

I highlight three features of the estimates. First, during 1969 through 1996, the negative comovement between stock returns and bond yields is not driven by macro news covariances. These covariances are around zero, whether slightly positive (one-year real and nominal yields) or slightly negative (seven-year nominal yield). These covariances are all statistically indistinguishable from zero. For each bond, the non-macro news covariances are strongly negative, both statistically and economically.

Second, during 1997 through 2019, the positive comovement between stock returns and bond yields is almost entirely accounted for macro news covariances. These are all positive and statistically different from zero. By contrast, non-macro news covariances are all close to zero, both economically and statistically.

Third, the only statistically reliable distinction between the two periods is the change in the non-macro news covariances. Although the macro news covariances are higher in the later period than in the earlier period, the differences are statistically insignificant. Moreover, the magnitudes of these differences are all small relative to the differences in non-macro news covariances.

Figure 3 illustrates the striking change from the first part of the sample to the second. Panel A displays for each quarter the product of the innovations of excess stock returns and changes in the one-year nominal yield spanned by the macroeconomic innovations. Think of these as “realized macro covariances,” in the sense that the sample macro news covariance
is the mean of these products. It also displays for each quarter the product of the residual innovations, or realized residual covariances. These are “realized non-macro news covariances.” Panel B displays the same information for the seven year nominal yield. Realized values for the one-year real yield are not displayed because they are similar to those for the one-year nominal yield.

Other than during the late 1970s, the realized macro covariances are consistently positive. Through approximately 1995, realized residual covariances are usually negative. In particular, the largest magnitude realizations (1982Q4 and 1971Q1) are negative residual realizations. After 1995, the realized residual covariances are much more muted.

These results are surprising and either encouraging or discouraging, depending on your perspective. The good news is that in the past 50 years there appears to be no regime shift in the relation between macroeconomic innovations and the comovement between stock returns and bond yields. Macro innovations generally induce a positive correlation. The bad news is that this macroeconomic factor model cannot explain why the relation between stock returns and bond yields changed substantially between the 1969—1996 period and the 1997—2019 period. The only clear difference is that a strong negative comovement produced by non-macro news in the early period disappears in the later period.

3.3 What types of macro news drive stock—bond comovement?

The model’s macroeconomic news consists of forecast revisions of current and future inflation, as well as current and future output. A natural question is whether one type of news is the primary driver of macro news covariances. Absent a structural model we cannot separate cleanly one type of news from another. Thus there is no unambiguous way to investigate the question using the previous section’s factor model.

However, it turns out that the data speak fairly clearly to this question, even though the question has no structural interpretation here. In brief, positive covariances between stock returns and changes in bond yields are associated with news about current and future GDP growth. By contrast, neither news about current nor future inflation has much of a connection to these macro news covariances.

I proceed by writing the macro news covariance between the excess stock return and the
change in, say, the yield on a seven-year nominal bond as (for the early sample period)

\[
\text{Cov} \left( \beta'_{m,E} \epsilon_t, \beta^{(7\text{yr})}'_{y,E} \epsilon_t \right) = \beta'_{m,E} \Omega_E \beta^{(7\text{yr})}_{y,E} \\
= \left( \beta'_{m,E} C_E \right) : \left( \beta^{(7\text{yr})}'_{y,E} C_E \right),
\]

where \( C_E C_E' \) is the Cholesky factorization of the covariance matrix of macroeconomic news in the early period. The Cholesky decomposition depends on the ordering of the columns of the macroeconomic news. For this exercise, the order is inflation PCs followed by output growth PCs. Within both groups, the order corresponds to the order of the PCs.

Both terms in parentheses in the last line of (15) are length-six vectors. Element-by-element multiplication of these vectors decomposes the macro news covariance into six components associated with the six orthogonalized macro variables.

Table 6 reports each of these decompositions. The sums of the rows equal the “Spanned by Macro News” covariances reported in Table 5. The most striking feature of the table is the dominant economic contribution of the second PC of output growth. For all three bonds and both time periods, the contribution of this PC to the macro news covariance is larger in absolute value than the contribution of any other PC. Moreover, the contribution of this PC is almost identical across the two sample periods.

Recall Figure 2, which displays the loadings of the principal components. The figure shows that this second PC of output growth is the most important PC for news about current and expected future output growth. (The first PC is almost entirely about past growth.) The Cholesky decomposition, which puts inflation first, strips out any inflation-related part to this news. Hence news of higher current and expected future output pushes up stock prices and bond yields, both real and nominal.

The contributions of the inflation PCs are more muted in the early period and practically nonexistent in the later period. In the early period, all of the asymptotic \( t \) statistics are below one in absolute value. Only one exceeds that value in the later period. The first and third output growth PCs have unstable contributions across the two periods. The contributions of the first output growth PC switch from small and negative in the early sample to small and positive in the later sample. The contributions of the third output PC switch from moderate and negative in the early period to approximately zero in the later period.
4 Inflation-centric Models of Comovement

The previous section’s evidence clearly documents that stock–bond comovement has little to do with stock–inflation comovement. Yet a substantial literature grounded in consumption-based asset pricing argues the opposite. This section unpacks the dissonance between this literature and the empirical evidence.

4.1 The literature

The relevant research starts with the observation that inflation was countercyclical throughout much of the second half of the 20th century, and more recently has been procyclical. Asset pricing implications of countercyclical inflation are explored by Piazzesi and Schneider (2007). They document that news about expected future consumption growth and news about expected future inflation are negatively correlated throughout much of the postwar period. Piazzesi and Schneider combine these dynamics with recursive preferences to produce an asset-pricing model that explains why the nominal yield curve slopes up on average: investor fear stagflation. Bansal and Shaliastovich (2013) use similar ingredients to build a term structure model that exhibits countercyclical expected inflation.

In long-run risk models that build on Bansal and Yaron (2004), the aggregate stock market reacts positively to news of higher expected future consumption growth. This relation, coupled with the evidence discussed in the prior paragraph and the Fisher equation linking expected inflation to nominal yields, produces a negative covariance between aggregate stock returns and nominal long-term yields.

Burkhardt and Hasseltoft (2012) modify this framework to explain why the stock–bond relation sometimes changes sign. They conclude that the correlation between consumption growth and inflation changes over time. From 1930 through 1970, the correlation between annual consumption growth and annual inflation ranges from positive to modestly negative. Subsequently the correlation turns sharply negative, in the neighborhood of $-0.6$ during 1970 through 2000. The correlation then switches sign again, to about 0.6 from 2000 through 2010. Burkhardt and Hasseltoft use this and related evidence to motivate a long-run risk model with exogeneous regimes shifts in inflation–output dynamics. They interpret the sign change

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2 Model parameterizations almost always exhibit a sufficiently high elasticity of intertemporal substitution to ensure this positive relation.
in the stock-bond covariance in the 1990s as a consequence of a shift from a countercyclical inflation regime to a procyclical inflation regime.

Other researchers follow the spirit of Burkhardt and Hasseltoft to explain Figure 1. Campbell, Sunderam, and Viceira (2017) use a continuous state variable to capture time-varying covariances with expected inflation rather than one that jumps from regime to regime. Song (2017) endogenizes regime shifts in inflation with regime shifts in monetary policy. David and Veronesi (2013) have unobserved regimes that differ in their exogeneous conditional covariance between inflation expectations and equity cash flows, creating a filtering problem for agents. Campbell, Pflueger, and Viceira (2020) combine habit formation preferences with an exogeneous regime shift in the dynamics of output and inflation.

These interpretations are appealing because they combine off-the-shelf asset pricing models with a well-documented change in stock–inflation dynamics. Table 1 reports that that stock returns and changes in expected one-year inflation are negatively correlated during 1969Q1 through 1996Q4. The sign is positive during 1997Q1 through 2019Q4.

Inflation-based approaches have difficulty explaining time-varying comovement of stock returns and real yields. However, data limitations prevent us from estimating properties of real yields as precisely as we estimate those of nominal yields. Therefore inconsistencies between empirical and model-implied properties of real yields are not necessarily glaring failures of these models.

4.2 Confronting Duffee (2018)

The sample covariance between stock returns and changes in annual expected inflation swings from negative to positive across the early and late sample periods. Yet Table 2 shows that the size of the change is less than a fifth the sizes of corresponding changes for covariances with changes in bond yields. The covariance varies little across these periods because from quarter to quarter, not much news is revealed about expected future inflation. The glaring failure of inflation-centric models is they require much more volatility of inflation news than we see in the data.

The evidence of Duffee (2018) foreshadows this conclusion, thus I first summarize the methodology in that research. Denote the log change in the price level from \( t - 1 \) to \( t \) as \( \pi_t \). Denote the log return to holding an \( n \)-period nominal bond from \( t \) to \( t + 1 \) in excess of the
short-term real rate and inflation as

\[ x_{r,y,t+1}^{(n)} \equiv (n y_t^{(n)} - (n-1) y_{t+1}^{(n-1)}) - r_t^{(1)} - \pi_{t+1}. \] (16)

A standard accounting identity first applied by Campbell and Ammer (1993) expresses the bond’s yield as the sum of future inflation, real rates, and excess returns,

\[ y_t^{(n)} = \frac{1}{n} \sum_{i=1}^{m} \pi_{t+i} + \frac{1}{n} \sum_{i=1}^{n} r_{t+i-1}^{(1)} + \frac{1}{n} \sum_{i=1}^{n} x_{r,y,t+i}^{(n-i+1)}. \] (17)

Conditioning (17) on information at time \( t \) produces

\[ E_t \left( y_t^{(n)} \right) = \frac{1}{n} \sum_{i=1}^{n} E_t \left( \pi_{t+i} \right) + \frac{1}{n} \sum_{i=1}^{n} E_t \left( r_{t+i-1}^{(1)} \right) + \frac{1}{n} \sum_{i=1}^{n} E_t \left( x_{r,y,t+i}^{(n-i+1)} \right). \] (18)

Equation (18) says that the period-\( t \) nominal yield is the sum of average expected future short-term real rates, average expected inflation, and average expected excess returns over the life of the bond.

Mechanically, innovations in yields must equal innovations in expected future inflation, real rates, and expected excess returns. The notation is

\[ \tilde{y}_t^{(n)} \equiv y_t^{(n)} - E_{t-1} y_t^{(n)}, \]

\[ = \eta_{\pi,t}^{(n)} + \eta_{r,t}^{(n)} + \eta_{xr,t}^{(n)}. \] (19)

The news components are

\[ \eta_{\pi,t}^{(n)} \equiv E_t \left( \frac{1}{n} \sum_{i=1}^{n} \pi_{t+i} \right) - E_{t-1} \left( \frac{1}{n} \sum_{i=1}^{n} \pi_{t+i} \right), \]

\[ \eta_{r,t}^{(n)} \equiv E_t \left( \frac{1}{n} \sum_{i=1}^{n} r_{t+i-1} \right) - E_{t-1} \left( \frac{1}{n} \sum_{i=1}^{n} r_{t+i-1} \right), \]

\[ \eta_{xr,t}^{(n)} \equiv E_t \left( \frac{1}{n} \sum_{i=1}^{n} x_{r,y,t+i}^{(n-i+1)} \right) - E_{t-1} \left( \frac{1}{n} \sum_{i=1}^{n} x_{r,y,t+i}^{(n-i+1)} \right). \] (20)

Use this accounting framework to decompose the conditional covariance between aggre-
gate stock returns and innovations in the $n$-maturity nominal bond yield. The conditional covariance is
\[
\text{Cov}_{t-1} \left( x_{r,m,t}, \tilde{y}^{(n)}_t \right) = \text{Cov}_{t-1} \left( x_{r,m,t}, \eta^{(n)}_{\pi,t} \right) + \text{Cov}_{t-1} \left( x_{r,m,t}, \eta^{(n)}_{r,t} \right) + \text{Cov}_{t-1} \left( x_{r,m,t}, \eta^{(n)}_{xr,t} \right).
\] (21)

Changes in the overall covariance over time must be driven by changes in one or more of the three component covariances. The literature discussed in the previous subsection focuses on the time-variation in first term on the right, the conditional covariance between stock returns and news about expected inflation.

The evidence in Duffee (2018) suggests that this approach may be incapable of capturing observed dynamics between stock returns and bond yields. That paper examines the unconditional variance decomposition of yield innovations, given by
\[
\text{Var}_{t-1} \left( \tilde{y}^{(n)}_t \right) = \text{Var}_{t-1} \left( \eta^{(n)}_{\pi,t} \right) + \text{Var}_{t-1} \left( \eta^{(n)}_{r,t} \right) + \text{Var}_{t-1} \left( \eta^{(n)}_{xr,t} \right) + 2\text{Cov}_{t-1} \left( \eta^{(n)}_{\pi,t}, \eta^{(n)}_{r,t} \right) + 2\text{Cov}_{t-1} \left( \eta^{(n)}_{\pi,t}, \eta^{(n)}_{xr,t} \right) + 2\text{Cov}_{t-1} \left( \eta^{(n)}_{r,t}, \eta^{(n)}_{xr,t} \right).
\] (22)

This earlier work concludes that the variance of news about expected inflation contributes little to the overall variance of yield innovations. The ratio of the first variance on the right to the total variance ranges from 0.1 to 0.2 across various sample periods and bond maturities.

In addition, Duffee (2018) calculates model-implied decompositions (22) for estimated models in Piazzesi and Schneider (2007) and Bansal and Shaliastovich (2013). Model-implied volatilities of yield shocks are well below observed volatilities, while simultaneously model-implied volatilities of news about expected future inflation are well above observed volatilities. In a nutshell, in the data, yield shocks are primarily driven by news other than revisions in inflation expectations, while these models rely on an inflation channel.

### 4.3 Properties of inflation-centric models

I perform a similar exercise for a few models that attempt to explain time-varying comovement of stock returns and nominal yields. Table 7 reports standard deviations of quarterly news about expected inflation and quarterly innovations in five-year Treasury bond yields. The first set of estimates use the approach of Duffee (2018), which relies on a minimal set of assumptions. The implied ratios of the variance of news about expected inflation to the
variance of yield innovations range from 0.03 to 0.13, with tight asymptotic standard errors.

The next set of standard deviations in the table are for the three regimes in the estimated model of Song (2017). The table reports that Song’s model generates standard deviations of quarterly nominal yield innovations similar to those reported by Duffee. However, it does so almost entirely through news about expected inflation. The inflation variance ratios are close to one for all regimes.

Like Song’s model with recursive preferences, the habit formation model of Campbell et al. (2020) roughly matches the volatility of quarterly nominal yield innovations. The habit formation preferences generate more news about expected excess bond returns than the recursive preferences employed by Song. Thus the ratios of inflation-news variance to yield-shock variance in Campbell et al. (2020) are a little larger than 0.8, improving slightly on the performance of Song (2017). Nonetheless, the standard deviation of inflation news for 1979–2001 is 2.5 times the standard deviation calculated using the approach of Duffee (2018). The corresponding ratio for 2001–2011 is 4.5. In sum, the models of Song (2017) and Campbell et al. (2020) match the observed volatility of yield innovations using stochastic processes for expected inflation that are unrealistically volatile.

Inflation variance ratios for the model of David and Veronesi (2013) are much smaller. It generates standard deviations of news about expected inflation that are not much larger than those based on Duffee (2018). Volatilities of yield innovations are a little low relative to the data, thus the model’s variance ratios are around 1/3. Their inflation-centric model generates more news about expected future real rates and expected future excess returns than either Song (2017) or Campbell et al. (2020). At first glance, this is surprising because David and Veronesi use power utility preferences rather than preferences that are commonly used to substantial variation in real rates and risk premia. How is this possible?

In David and Veronesi (2013), nominal bonds are essentially leveraged bets on future inflation. They follow Basak and Yan (2010) by assuming investors have a form of money illusion. When investors’ expectations of next period’s inflation increase by, say, one percent, they revise downward their expectation of next period’s real stochastic discount factor (SDF) by 80 basis points, and their expectation of next period’s nominal SDF by 180 basis points. Thus the short-term real rate rises by 80 basis points and the short-term nominal rate rises by 180 basis points.

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3 Thanks to Dongho for sharing the standard deviations underlying his Table E-7.
4 I produce these numbers by modifying the Matlab code written by Carolyn, available on the JPE website.
180 basis points. In the model, changes in one-year real yields, expected annual inflation, and one-year real yields are almost perfectly correlated, with standard deviations proportional to 0.8, 1, and 1.8.

Sophisticated bond-trading organizations employ many finance PhDs. We need to do a better job teaching our students if money illusion significantly affects how they value real and nominal bonds. Thankfully (at least pedagogically), the model’s requirement that real yields and expected inflation move in lockstep has no empirical support. Their changes are not even positively correlated. Using Bank of England data, Barr and Campbell (1997) estimate that monthly innovations in one-year real rates and one-year inflation expectations are negatively correlated. Table 1 confirms the same negative correlation during 1969 through 1996. The correlation during 1997 through 2019 is approximately zero. Hence the key mechanism in David and Veronesi (2013) is just as implausible as are the mechanisms in Song (2017) and Campbell et al. (2020).

5 Concluding comments

Sign changes in the correlation between stock returns and bond yields were first recognized twenty years ago. Standard asset-pricing theories connect these sign changes to variations in macroeconomic dynamics. These theories usually place inflation dynamics on the center stage. However, the empirical analysis here concludes that dynamics of news about current and expected future output growth and inflation are unrelated to these sign changes. This conclusion is particularly strong for inflation dynamics. In contrast to news about output growth, news about inflation has little connection to the comovement between stocks and bonds. Theories that rely on changing inflation dynamics to explain sign changes in stock–bond comovement rely on unrealistic inflation properties.

Appendix

This appendix presents additional information about the construction of the macroeconomic innovations. Respondents to the SPF in the middle of quarter \( t \) predict levels of nominal GDP and the GDP price index for quarters \( t + i, i = -1, \ldots, 4 \). A forecaster’s prediction of the level of real GDP for quarter \( t+i \) is defined as the ratio of the prediction of nominal GDP
to the prediction of the price level. I define consensus forecasts of levels of real GDP and the GDP price index as mean forecasts calculated after dropping any individual forecasts that are more than two standard deviations from the full-sample mean.

The consensus forecast at \( t \) of real GDP growth (inflation) for quarter \( t + i \) is defined as the log difference between the consensus forecast at \( t \) of \( t + i \)'s level of real GDP (price index) and the consensus forecast at \( t \) of \( t + i - 1 \)'s level of real GDP (price index). For \( i = -1 \), this calculation requires a consensus prediction at \( t \) for the level of real GDP at \( t - 2 \). The SPF does not ask forecasters to predict two-quarter-earlier values, since NIPA has already released its final estimates for that quarter. Therefore I use the previous quarter’s consensus prediction for quarter \( t - 2 \). This consensus prediction is typically the NIPA preliminary forecast, available to SPF forecasters at \( t - 1 \). Quarterly macroeconomic innovations at \( t \) are defined as the change from quarter \( t - 1 \) to quarter \( t \) in the real output growth and inflation consensus forecasts for quarters \( t - 1 \) through \( t + 3 \). Additional construction details are in the online Appendix.
References

Ang, Andrew, Geert Bekaert, and Min Wei, 2007, Do macro variables, asset markets or surveys forecast inflation better?, *Journal of Monetary Economics* 54, 1163-1212.


Table 1. Second moments of U.S. stock returns, expected inflation, and interest rates

The table reports standard deviations and correlations among quarterly excess returns to the U.S. stock market, changes in a one-year inflation forecast, and changes in zero-coupon bond yields. The one-year real yield is the one-year nominal yield less consensus forecasts of one-year inflation from the Survey of Professional Forecasters. Excess stock returns are measured in percent per quarter. Expected inflation and yields are measured in percent per year. Standard deviations are on the diagonal and correlations are off the diagonal.

<table>
<thead>
<tr>
<th></th>
<th>Stock Return</th>
<th>1 Yr Real Yield</th>
<th>1 Yr Infl Forecast</th>
<th>1 Yr Nom Yield</th>
<th>7 Yr Nom Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>1969Q1 — 1996Q4 (112 obs)</td>
<td>8.47</td>
<td>-0.15</td>
<td>1.06</td>
<td>-0.07</td>
<td>-0.15</td>
</tr>
<tr>
<td></td>
<td>-0.18</td>
<td>0.94</td>
<td>0.20</td>
<td>1.07</td>
<td>0.86</td>
</tr>
<tr>
<td>1997Q1—2019Q4 (92 obs)</td>
<td>7.38</td>
<td>0.37</td>
<td>0.36</td>
<td>0.15</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>0.30</td>
<td>0.49</td>
<td>0.24</td>
<td>0.54</td>
<td>0.41</td>
</tr>
</tbody>
</table>
Table 2. Tests of covariance stability

The table reports covariances with quarterly excess returns for changes in a one-year inflation forecast and changes in zero-coupon bond yields. The one-year real yield is the one-year nominal yield less consensus forecasts of one-year inflation from the Survey of Professional Forecasters. Excess stock returns are measured in percent per quarter. Expected inflation and yields are measured in percent per year. The standard error of the difference between two covariances is estimated using GMM. In brackets are $p$-values of asymptotic tests that the difference is zero.

<table>
<thead>
<tr>
<th></th>
<th>One Year Real Yield</th>
<th>One Year Expected Inflation</th>
<th>One Year Nominal Yield</th>
<th>Seven Year Nominal Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>1969Q1 – 1996Q4</td>
<td>−1.36</td>
<td>−0.22</td>
<td>−1.59</td>
<td>−1.40</td>
</tr>
<tr>
<td>1997Q1 – 2019Q4</td>
<td>1.00</td>
<td>0.17</td>
<td>1.16</td>
<td>0.90</td>
</tr>
<tr>
<td>Difference</td>
<td>2.36</td>
<td>0.39</td>
<td>2.75</td>
<td>2.30</td>
</tr>
<tr>
<td>Std Error</td>
<td>(1.03)</td>
<td>(0.50)</td>
<td>(1.10)</td>
<td>(0.78)</td>
</tr>
<tr>
<td>$p$-value</td>
<td>[0.022]</td>
<td>[0.438]</td>
<td>[0.013]</td>
<td>[0.003]</td>
</tr>
</tbody>
</table>
Table 3. Summary statistics of macroeconomic news

Quarterly changes in forecasts of real GDP growth (log first differences of quarterly real GDP) and inflation (log first differences of the quarterly GDP price index) are calculated from the Survey of Professional Forecasters. Forecast revisions at $t$ are made for quarters $t - 1$ through $t + 3$. Real GDP growth and inflation are measured in percent per quarter. The sample period is 1969Q1 through 2019Q4. Five observations with missing four-quarter-ahead forecast innovations are dropped. Panel A reports split-sample standard deviations. For Panel B, principal components are calculated separately for the covariances matrices of GDP growth innovations and inflation innovations. Both covariances are for the full sample of 199 nonmissing observations from 1969Q1 through 2019Q4.

Panel A. Standard deviations of forecast innovations

<table>
<thead>
<tr>
<th>Quarters Ahead</th>
<th>1</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1969Q1 — 1996Q4 (107 obs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP Growth</td>
<td>0.83</td>
<td>0.32</td>
<td>0.25</td>
<td>0.21</td>
<td>0.20</td>
</tr>
<tr>
<td>Inflation</td>
<td>0.47</td>
<td>0.17</td>
<td>0.14</td>
<td>0.12</td>
<td>0.13</td>
</tr>
<tr>
<td>1997Q1 — 2019Q4 (92 obs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP Growth</td>
<td>0.73</td>
<td>0.22</td>
<td>0.14</td>
<td>0.08</td>
<td>0.09</td>
</tr>
<tr>
<td>Inflation</td>
<td>0.29</td>
<td>0.08</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Panel B. Explanatory Power of Principal Components

<table>
<thead>
<tr>
<th>Contribution to Variance (percent)</th>
<th>1st PC</th>
<th>2nd PC</th>
<th>3rd PC</th>
<th>4th PC</th>
<th>5th PC</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP Growth</td>
<td>78.6</td>
<td>12.0</td>
<td>5.3</td>
<td>2.8</td>
<td>1.3</td>
</tr>
<tr>
<td>Inflation</td>
<td>78.5</td>
<td>15.1</td>
<td>3.0</td>
<td>1.8</td>
<td>1.5</td>
</tr>
</tbody>
</table>
Table 4. Explanatory power of macroeconomic news for stock returns and changes in bond yields

Quarterly excess returns to the U.S. stock market and changes in zero-coupon bond yields are regressed on six contemporaneous revisions in survey forecasts of future economic growth and inflation. The table reports $R^2$ of these regressions for two sample periods. The one-year real yield is the one-year nominal yield less consensus forecasts of one-year inflation from the Survey of Professional Forecasters.

<table>
<thead>
<tr>
<th></th>
<th>1969Q1–1996Q4</th>
<th>1997Q1—2019Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(107 obs)</td>
<td>(92 obs)</td>
</tr>
<tr>
<td>Excess stock return</td>
<td>0.12</td>
<td>0.34</td>
</tr>
<tr>
<td>One year real yield</td>
<td>0.33</td>
<td>0.31</td>
</tr>
<tr>
<td>One year nominal yield</td>
<td>0.38</td>
<td>0.43</td>
</tr>
<tr>
<td>Seven year nominal yield</td>
<td>0.24</td>
<td>0.29</td>
</tr>
</tbody>
</table>
Quarterly excess returns to the U.S. stock market and changes in zero-coupon bond yields are explained by contemporaneous macroeconomic news, measured by six principal components of revisions in survey forecasts of real output growth and inflation. Covariances between stock returns and changes in bond yields are decomposed into a component spanned by macroeconomic news and a component orthogonal to the news. The table reports these components with GMM asymptotic standard errors are in parentheses.

<table>
<thead>
<tr>
<th>Sample [Observations]</th>
<th>Bond</th>
<th>Spanned by Macro News</th>
<th>Orthogonal to Macro News</th>
</tr>
</thead>
<tbody>
<tr>
<td>1969Q1 – 1996Q4</td>
<td>1 year real</td>
<td>0.40</td>
<td>−1.78**</td>
</tr>
<tr>
<td>[107]</td>
<td></td>
<td>(0.63)</td>
<td>(0.85)</td>
</tr>
<tr>
<td></td>
<td>1 year nominal</td>
<td>0.23</td>
<td>−1.80**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.72)</td>
<td>(0.82)</td>
</tr>
<tr>
<td></td>
<td>7 year nominal</td>
<td>−0.13</td>
<td>−1.31**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.34)</td>
<td>(0.62)</td>
</tr>
<tr>
<td>1997Q1 – 2019Q4</td>
<td>1 year real</td>
<td>0.82***</td>
<td>0.18</td>
</tr>
<tr>
<td>[92]</td>
<td></td>
<td>(0.29)</td>
<td>(0.14)</td>
</tr>
<tr>
<td></td>
<td>1 year nominal</td>
<td>0.92**</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.44)</td>
<td>(0.15)</td>
</tr>
<tr>
<td></td>
<td>7 year nominal</td>
<td>0.66***</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.24)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>Test of Equality</td>
<td>1 year real</td>
<td>0.42</td>
<td>1.95**</td>
</tr>
<tr>
<td>Across Samples</td>
<td></td>
<td>(0.70)</td>
<td>(0.86)</td>
</tr>
<tr>
<td></td>
<td>1 year nominal</td>
<td>0.70</td>
<td>2.04**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.85)</td>
<td>(0.83)</td>
</tr>
<tr>
<td></td>
<td>7 year nominal</td>
<td>0.79*</td>
<td>1.56**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.42)</td>
<td>(0.65)</td>
</tr>
</tbody>
</table>
Table 6. Contributions of Macroeconomic News to Stock—Bond Covariances

Quarterly excess returns to the U.S. stock market and changes in zero-coupon bond yields are explained by contemporaneous macroeconomic news, measured by principal components (PCs) of revisions in survey forecasts of inflation (three PCs) and real output growth (three additional PCs). A Cholesky decomposition orthogonalizes the news with inflation news ordered ahead of output growth news. The table reports the contribution of each principal component to the covariances. Asymptotic standard errors are in parentheses.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Bond</th>
<th>Inflation PCs</th>
<th>Output Growth PCs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>1969Q1 – 1996Q4</td>
<td>1 year real</td>
<td>−0.02</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.11)</td>
<td>(0.20)</td>
</tr>
<tr>
<td></td>
<td>1 year nominal</td>
<td>−0.09</td>
<td>−0.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.18)</td>
<td>(0.20)</td>
</tr>
<tr>
<td></td>
<td>7 year nominal</td>
<td>−0.05</td>
<td>−0.16</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.11)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>1997Q1 – 2019Q4</td>
<td>1 year real</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td></td>
<td>1 year nominal</td>
<td>−0.05</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.04)</td>
<td>(0.16)</td>
</tr>
<tr>
<td></td>
<td>7 year nominal</td>
<td>0.01</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.05)</td>
<td>(0.16)</td>
</tr>
</tbody>
</table>
Table 7. Standard deviations of news about expected inflation and yield innovations

Standard deviations of quarterly shocks to both expected average inflation over the next five years and the five-year Treasury yield are reported for various models. The units are basis points of annualized rates. The column labeled “Variance Ratio” reports the squared ratio of the two standard deviations. In parentheses are asymptotic standard errors for variance ratios calculated as in Duffee (2018). They are computed with GMM. In David and Veronesi (2013) the regime is unobserved, hence agents have conditional probabilities that the current regime is regime \( i \). The regime-specific values reported in the table are conditional on agents assigning at least a 0.5 probability that the current regime is the listed regime.

<table>
<thead>
<tr>
<th>Source</th>
<th>Period and/or Regime</th>
<th>Inflation News</th>
<th>Yield Innovations</th>
<th>Variance Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.037)</td>
</tr>
<tr>
<td></td>
<td>1979Q3–2001Q1</td>
<td>24</td>
<td>74</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.034)</td>
</tr>
<tr>
<td></td>
<td>2001Q2–2011Q4</td>
<td>8</td>
<td>45</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>Countercyclic/Active Fed</td>
<td>79</td>
<td>71</td>
<td></td>
<td>1.22</td>
</tr>
<tr>
<td>Countercyclic/Passive Fed</td>
<td>104</td>
<td>99</td>
<td></td>
<td>1.12</td>
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<tr>
<td>Procyclic/Active Fed</td>
<td>44</td>
<td>54</td>
<td></td>
<td>0.65</td>
</tr>
<tr>
<td>Campbell et al. (2020)</td>
<td>1979Q3–2001Q1</td>
<td>59</td>
<td>66</td>
<td>0.81</td>
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<tr>
<td></td>
<td>2001Q2–2011Q4</td>
<td>37</td>
<td>40</td>
<td>0.85</td>
</tr>
<tr>
<td>Unconditional</td>
<td>28</td>
<td>47</td>
<td></td>
<td>0.35</td>
</tr>
<tr>
<td>Regime 1</td>
<td>18</td>
<td>29</td>
<td></td>
<td>0.38</td>
</tr>
<tr>
<td>Regime 2</td>
<td>39</td>
<td>66</td>
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<td>0.35</td>
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<tr>
<td>Regime 3</td>
<td>26</td>
<td>43</td>
<td></td>
<td>0.36</td>
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<td>Regime 4</td>
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<td>104</td>
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<td>0.31</td>
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<td>Regime 5</td>
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<td>0.40</td>
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<tr>
<td>Regime 6</td>
<td>27</td>
<td>48</td>
<td></td>
<td>0.32</td>
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</table>
Figure 1. Rolling sample correlations between daily stock returns and changes in nominal Treasury yields

The figure displays sample correlations between the daily return to the U.S. aggregate stock market and daily changes in the yield on a seven-year zero-coupon nominal Treasury bond. The samples are overlapping periods of 44 days.
Figure 2. Principal Components of Forecast Innovations to Real GDP Growth and Inflation

Forecast innovations are consensus SPF forecasts at quarter $t$ of real output growth and inflation for quarters $t+i$, $i = -1, \ldots, 3$, less consensus forecasts for the same quarters made at quarter $t - 1$. Both output growth and inflation are expressed in percent per quarter. The data range from 1969Q1 through 2019Q4. The figure displays loadings of the principal components scaled by their standard deviations.
Figure 3. Quarterly products of excess stock returns and changes in nominal yields

The excess return to the aggregate U.S. market is in percent/quarter. Yields, in percent/year, are from Gurkaynak et al. (2007). Both the stock return and quarterly changes in yields are regressed on contemporaneous shocks to survey forecasts of GDP growth and inflation. Details are in the text. “Macro-spanned” refers to the products of fitted values from the regressions and “Residuals” refers to the products of residuals from the regressions.