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# Long–Short Sensitivity in the Term Structure

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Abstract

The expected change of a long-maturity Treasury yield conditional on the contemporaneous change of a short-maturity Treasury yield varies widely during the past 60 years. The projection coefficient ranges from around 0.2 in the mid-1960s to well above 1.0 in the late 1990s. Accompanying this long upward time trend are considerable swings over the course of a few years. This variation appears to be connected to changing reactions of yields to real-side news and monetary policy shocks, but straightforward stories such as changes in monetary policy regimes do not appear consistent with the evidence.

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# 1 Introduction

How do innovations in long-term Treasury yields covary with innovations in short-term Treasury yields? The empirical properties of this joint variation help distinguish among different economic theories of the term structure. In this research I examine regressions of short-horizon (daily and monthly) changes in long-term yields on contemporaneous changes in short-term yields, focusing on the estimated coefficient's variation over time. Conceptually similar exercises first appear in Estrella and Hardouvelis (1990) and Thorton (2018), who estimate rolling regressions of changes in Treasury bond yields on contemporaneous changes in the Fed funds rate.[1] The analysis here closely relates to Hanson, Lucca, and Wright (2021), as discussed in more detail below.

Figure 1 sets the stage for the analysis. It displays parameter estimates from rolling regressions of one-day and one-month changes in the seven-year Treasury yield on corresponding changes in the one-year Treasury yield. The sample ranges from June 1961 through September 2008. I cut the sample off at this date because term structure dynamics shift substantially at the onset of the Great Recession owing to the zero lower bound.

The figure reveals remarkably wide variation over time in the regression coefficient, which I label "long–short sensitivity." It hovers around 0.3 through the mid-1960s, then rises erratically through the late 1980s until it reaches about 1.0. During the 1990s and 2000s, long–short sensitivity ranges from around 0.5 (the late 1990s) to about 1.5 (the early 2000s).

A no-arbitrage term structure model provides a useful lens to interpret this evidence. The level of long–short sensitivity is increasing in the persistence of short-rate innovations under the equivalent-martingale measure. We can think of the regression coefficient as an overall measure of this persistence, integrated across all innovations to the state variables driving the short rate. Therefore the coefficient depends on both the conditional covariance matrix of these innovations and the $\mathbb{Q}$-persistence of the individual innovations. Evidence drawn from the existing term structure literature points to variation in conditional covariance matrices rather than variation in $\mathbb{Q}$-persistence as the primary driver of the patterns in Figure 1.

Stories involving time-varying volatilities easily spring to mind. Different types of news have different implications for long–short sensitivity. News about technological change and news about long-run inflation can produce high sensitivity through real and inflation-

[1] The earliest version of Thorton (2018) appeared in 2007.

expectation channels respectively. Transitory supply disruptions and monetary policy shocks can produce low sensitivity. Hanson and Stein (2015) add the important caveat (applied in their case to monetary policy shocks) that news can simultaneously affect physical expectations of future short rates and bond risk premia, complicating equivalent-martingale dynamics. Changes over time in the relative importance of these types of news will drive corresponding changes in long–short sensitivity.

Armed with this logic, I investigate empirically the links between the macroeconomy and long–short sensitivity. The evidence here points to a real-side explanation for time-varying sensitivity, although the nature of that explanation remains elusive.

The first set of results attempt to explain variations in long–short sensitivity with measures of conditional macroeconomic volatility and real output. The general upward trend in long–short sensitivity since 1961 coincides with the Great Moderation's declining real-side volatility. Yet aside from that trend, there are no robust connections between long–short sensitivity and either broad measures of macroeconomic volatility or the level of macroeconomic activity.

Reactions to macroeconomic announcements provide stronger evidence tying long–short sensitivity to real-side macroeconomic news. Consider a nonfarm payroll announcement on day $t$ that exceeds expectations. Bond yields of all maturities typically increase in response to this news. Condition these responses on the level of long–short sensitivity for days surrounding day $t$, excluding day $t$. Label this neighborhood sensitivity "overall" sensitivity, in the sense that the local regression coefficient integrates over all innovations on these dates.

Payroll announcements occurring at times when overall sensitivity is higher are accompanied by smaller responses of one-year yields. Responses of seven-year yields to the announcements do not vary with overall sensitivity. Therefore "announcement-specific" sensitivity of nonfarm payroll surprises is high when overall long–short sensitivity is high. By contrast, announcement-specific sensitivity of inflation news (CPI, PPI, and their core counterparts) is unrelated to overall sensitivity.

This evidence suggests that high-sensitivity periods are characterized by a different mix of real-side news, but not inflation news, then are low-sensitivity periods. Some real-side news corresponds to high $\mathbb{Q}$-persistent innovations to rates, while other real-side news corresponds to low $\mathbb{Q}$-persistent innovations. When overall sensitivity is high, conditional volatilities of the latter types of real-side news are high relative to conditional volatilities of the former types.

Intriguingly, the wedge between announcement-specific sensitivities to real news and inflation news has a counterpart with two types of FOMC news. Responses of yields to Fed funds surprises on FOMC days vary systematically across periods of low and high overall sensitivity. Seven-year yields respond more strongly to Fed funds surprises when overall sensitivity is high, hence Fed funds announcement-specific sensitivity tracks overall sensitivity. However, announcement-specific sensitivity to forward guidance surprises is unrelated to overall sensitivity.

These results point to a straightforward monetary policy interpretation of variations in long–short sensitivity. The central bank's policy rule varies over time in aggressiveness towards real-side shocks. When the rule is more (less) aggressive, real-side news has relatively large (small) effects on near-term forecasts of short rates and smaller (larger) effects on longer-term forecasts. Similarly, a monetary policy shocks under an aggressive regime are anticipated to die out more quickly than are such shocks under a less-aggressive regime. However, the patterns in Figure 1 do not line up well with previously identified regime shifts in the central bank's policy strategies. Nor is there an intuitive reason why aggressiveness to real-side shocks will vary without corresponding variation in aggressiveness to inflation shocks.

As noted above, high long–short sensitivity corresponds to high $\mathbb{Q}$-persistence of short-rate innovations. Under the physical measure this can be explained both by high $\mathbb{P}$-persistence and a positive relation between short-rate innovations and bond risk premia. These are not mutually exclusive explanations. Even in a 65-year sample, conditional estimates of long-run short-rate persistence and risk premia are accompanied by fairly large standard errors. That said, the data point clearly towards higher $\mathbb{P}$-persistence when sensitivity is high. Point estimates do not support a significant risk premium interpretation, but the standard errors cannot rule one out.

Hanson et al. (2021) arrive at a substantially different conclusion in their analysis of long–short sensitivity. They focus on the 2000 through 2019 sample, documenting that regression coefficients of changes in longer-term yields on shorter-term yields decrease significantly with the horizon over which the changes are measured. This evidence is consistent with a positive relation between short-rate innovations and risk premia, which they argue is driven by slow-moving capital in the fixed-income sector.

My interpretation of this recent period differs from (and is less economically interesting than) the interpretation of Hanson et al. (2021). In brief, the sample yield dynamics were highly unusual. Two large and long-lasting events dominate the 2000 and later period. During both events (2000 through mid-2005 and October 2007 through 2017), shorter-term yields dropped steadily and substantially over two years, flattened out, and eventually rose. I find that short-horizon (daily) long–short sensitivity varied systematically during these events, creating the patterns observed by Hanson et al. (2021).

The next section provides some introductory evidence on long–short sensitivity. Section 3 provides intuition from no-arbitrage term structure models. Section 4 examines macroeconomic connections. Section 5 takes a close look at term structure properties during the 21st century. Section 6 concludes.

# 2 An Empirical Overview

I use changes in yields as proxies for innovations in equivalent-martingale expectations of future short rates. To derive the relationship between changes in yields and innovations, define the innovation from $t-1$ to $t$ in $\mathbb{Q}$-expected average short rates over $T$ periods as

$$\Delta E_t^{\mathbb{Q}}\left(\overline{r}(T)\right) \equiv E_t^{\mathbb{Q}}\left(\frac{1}{T}\sum_{h=t}^{t-1+T} r_h\right) - E_{t-1}^{\mathbb{Q}}\left(\frac{1}{T}\sum_{h=t}^{t-1+T} r_h\right). \tag{1}$$

The first $\mathbb{Q}$-expectation on the right is, aside from convexity, the yield at $t$ on a $T$-period bond. The second $\mathbb{Q}$-expectation is the period-$(t-1)$ expectation of this yield (again, aside from convexity). We do not observe this expectation, but we observe the period-$(t-1)$ yield on a $T$-period bond.

Rewrite (1) to connect it to changes in yields as

$$\Delta E_t^{\mathbb{Q}}\left(\overline{r}(T)\right) = \left(E_t^{\mathbb{Q}}\left(\frac{1}{T}\sum_{h=t}^{tf-1+T} r_h\right) - E_{t-1}^{\mathbb{Q}}\left(\frac{1}{T}\sum_{h=t-1}^{t-2+T} r_h\right)\right) - \frac{1}{T}\left(E_{t-1}^{\mathbb{Q}}(r_{t-1+T}) - r_{t-1}\right). \tag{2}$$

The large term in parentheses on the right of (2) is close to the first difference of the $T$-maturity yield because convexity at $t$ differs little from convexity at $t-1$. The magnitude of the second term is determined by $T$. For example, using daily data with $T$ equal to one year, the second term is the $\mathbb{Q}$-expected short rate in 365 days less the current short rate, divided by 365. Hence second term on the right is small when $T$ is large, either because the horizon is long in calendar terms or the data are high frequency.

I therefore apply the approximation

$$\Delta E_t^{\mathbb{Q}}\left(\overline{r}(T)\right) \approx y_t^{(T)} - y_{t-1}^{(T)} \tag{3}$$

using maturities sufficiently long that the second term on the right of (2) is irrelevant. Approximate the conditional projection of the innovation in long-horizon expected short rates on the contemporaneous innovation in shorter-maturity expected short rates as

$$\begin{aligned}\mathrm{Proj}_t\left(\Delta E_t^{\mathbb{Q}}\left(\overline{r}(T^{\mathrm{long}})\right)\middle|\Delta E_t^{\mathbb{Q}}\left(\overline{r}(T^{\mathrm{short}})\right)\right) =& \mathrm{Proj}_t\left(\Delta y_t^{(\mathrm{long})}\middle|\Delta y_t^{(\mathrm{short})}\right)\\ =& S_t \Delta y_t^{(\mathrm{short})}\end{aligned} \tag{4}$$

where the dependence of long–short sensitivity $S_t$ on the maturities is implicit. The conditional regression form is

$$\Delta y_t^{(\mathrm{long})} = S_t \Delta y_t^{(\mathrm{short})} + e_t. \tag{5}$$

Empirical implementation of (5) uses maturities of seven years and one year. Data availability determines the choice of long horizon. Standard datasets of Treasury yields begin in 1961. Gürkaynak, Sack, and Wright (2007) argue that owing to the maturity structure of Treasury coupon bonds, yields for zero coupon bonds are reliable for maturities greater than seven years only after August 1971. The one-year horizon ensures that the approximation (3) is accurate. Zero-coupon yields are interpolated by the Federal Reserve Board following the procedure of Gürkaynak, Sack, and Wright (2007).

Figure 1, discussed in Section 1, estimates $S_t$ using fixed-coefficient rolling regressions

$$\Delta y_t^{(7yr)} = S \Delta y_t^{(1yr)} + e_t. \tag{6}$$

The estimate for day $t$ uses 80 observations of daily changes in yields from trading day $t-79$ to trading day $t$. The estimate for month $t$ uses 36 observations of monthly changes in yields from month $t-35$ to month $t$. Regression (6) does not include constant terms to avoid throwing away information about the common trend in one-year and seven-year yields. This choice is consistent with (4).

Before attempting to link variations in long–short sensitivity to macroeconomic trends, it helps to understand other differences between high-sensitivity periods and short-sensitivity periods. I estimate (6) using daily data for each calendar quarter. This produces regression coefficients for all 190 quarters from 1961Q2 through 2008Q3. I then sort the 190 quarters into four groups formed by quartile break points of the coefficient.

Within a group, I construct a panel of observations of daily changes in the one-year yield and contemporaneous changes in instantaneous forward rates calculated by Gürkaynak et al. (2007). For each quartile group, I regress daily changes in instantaneous forward rates on daily changes in the one-year Treasury yield,

$$\Delta f_t^{(h\ yr)} = S_h \Delta y_t^{(1yr)} + e_t^{(h)}, \qquad h = 1, \ldots 7. \tag{7}$$

Panel A of Figure 2 displays the standard deviations of daily changes in forward rates. These volatilities vary substantially across the quartile groups, but not in a way that lines up cleanly with the quartile index. The quartile with the lowest quarterly long–short sensitivities has (for the most part) the smallest volatilities, while the quartile with second-lowest long–short sensitivities has the largest volatilities.

Panel B of Figure 2displays the estimated regression coefficients from (7). The panel shows, not surprisingly, that the implied $\mathbb{Q}$-persistence of short-rate innovations varies sharply across the quartiles. Consider quartile 1 (lowest quarterly long–short sensitivities). For this quartile, forward-rate sensitivities die out monotonically and quickly. The four-year instantaneous forward rate is largely insensitive to the one-year yield. Forward-rate sensitivities for quartile 4 rise with maturity, then decline slowly. The coefficients exceed one for all displayed maturities.

The next section uses a no-arbitrage framework to put formal structure on the different yield dynamics embodied by Figure 2.

# 3 Some No-Arbitrage Intuition

An economic theory designed to explain the patterns in Figures 1 and 2 requires considerable time-variation in yield dynamics. This section uses intuition from no-arbitrage term structure models to put some structure on admissible theories. To preview the results, variations in long–short sensitivity can be produced by both variations in the covariance matrix of innovations to state variables that drive yields and variations in the equivalent-martingale persistence of these state variables. Evidence in the term structure literature points to the former channel rather than the latter.

### 3.1 A Canonical Discrete Time Gaussian Setting

The absence of arbitrage implies that the yield of a default-free $m$-period zero-coupon bond is

$$y_t^{(m)} \equiv -\frac{1}{m}\log P_t^{(m)} = -\frac{1}{m}\log\left(E_t^{\mathbb{Q}}\left(e^{-\sum_{i=0}^{m-1} r_{t+i}}\right)\right), \tag{8}$$

where the $r_t$ is the one-period interest rate and $\mathbb{Q}$ superscript refers to an expectation under the equivalent-martingale measure. Inspection of (8) reveals that the yield equals the $\mathbb{Q}$-expected mean short rate over the life of the bond, adjusted for convexity. The convexity adjustment is small for maturities studied in this paper.[2]

Dynamics of the short rate determine the long–short sensitivity. The Gaussian framework of Joslin, Singleton, and Zhu (2011) helps us understand what properties of these dynamics are plausibly associated with variation in the long–short sensitivity. An $n$-dimensional state vector denoted $x_t$ drives variations in the short rate. The individual elements of $x_t$ have no economic content because the vector can be translated, scaled and rotated without any observable implications. Fundamental factors (e.g., the state of the macroeconomy; risk-bearing capacity of financial intermediaries) are unspecified combinations of the canonical factors. The canonical model of Joslin et al. (2011) rotates and scales the state vector such that the short rate is

$$r_t = \overline{r}^{\mathbb{Q}} + \iota' x_t \tag{9}$$

where $\iota$ is an $n$-vector of ones.

The state's dynamics under the physical measure are

$$x_t = \mu + \phi x_{t-1} + \epsilon_t, \qquad \epsilon_t \sim N(0, \Sigma). \tag{10}$$

[2] The Internet Appendix uses a back of the envelope calculation to estimate this adjustment is less than 20 annualized b.p. for the ten-year yield.

The covariance matrix $\Sigma$ is positive definite but otherwise unrestricted. Bonds are priced by the state's dynamics under the equivalent martingale measure,

$$x_t = \phi^{\mathbb{Q}} x_{t-1} + \epsilon_t^{\mathbb{Q}}, \qquad \epsilon_t^{\mathbb{Q}} \sim N(0, \Sigma). \tag{11}$$

Identifying assumptions in the canonical model are the absence of a constant term in (11), a lower triangular $\phi$ and a $\phi^{\mathbb{Q}}$ determined entirely by its eigenvalues. For example, if the eigenvalues are real and distinct, the matrix is diagonal with eigenvalues $d_1$ through $d_n$ on the diagonal,

$$\phi^{\mathbb{Q}} = \operatorname{diag}( \begin{array}{ccc} d_1 & \ldots & d_n \end{array} ). \tag{12}$$

The matrix $\phi^{\mathbb{Q}}$ determines the speed of mean reversion of the state vector under $\mathbb{Q}$-dynamics. Forecasts of the state under $\mathbb{Q}$ are

$$E_t^{\mathbb{Q}} x_{t+j} = \left(\phi^{\mathbb{Q}}\right)^j x_t. \tag{13}$$

For the case of real and distinct eigenvalues, plug (12) into (13) to produce element-by-element forecasts,

$$E_t^{\mathbb{Q}} \begin{pmatrix} x_{1,t+j} \\ \vdots \\ x_{n,t+j} \end{pmatrix} = \begin{pmatrix} d_1^j x_{1,t} \\ \vdots \\ d_n^j x_{n,t} \end{pmatrix}. \tag{14}$$

Therefore eigenvalue $i$ determines the speed of mean reversion under $\mathbb{Q}$ for element $i$ of the canonical state vector. Joslin et al. (2011) show that the eigenvalues of the canonical $\phi^{\mathbb{Q}}$ determine the speed of mean reversion under $\mathbb{Q}$ of all rotations of the canonical state vector.

In this homoskedastic model the convexity adjustment in (8) is constant over time. Therefore the bond's yield is

$$\begin{aligned} y_t^{(m)} =& c^{(m)} + \frac{1}{m} \sum_{i=0}^{m-1} E_t^{\mathbb{Q}} r_{t+i} \\ =& c^{(m)} + \overline{r}^{\mathbb{Q}} + \frac{1}{m} \left( \iota' \sum_{i=0}^{m-1} \left(\phi^{\mathbb{Q}}\right)^i \right) x_t \\ =& c^{(m)} + \overline{r}^{\mathbb{Q}} + \frac{1}{m} \left(I - \left(\phi^{\mathbb{Q}}\right)^m\right) \left(I - \phi^{\mathbb{Q}}\right)^{-1} x_t \end{aligned} \tag{15}$$

where the $m$-dependent constant term on the right is the convexity adjustment. Thus, bond yields are (aside from a constant) averages of equivalent-martingale expectations of short rates over the life of the bond.

Similarly, the one-period forward rate at $t$ for lending from $t+m$ to $t+m+1$ is (again, aside from a constant) the equivalent-martingale expectation of the $m$-ahead short rate. Formally,

$$\begin{aligned} f_t^{(m)} =& c^{(m+1)} - c^{(m)} + E_t^{\mathbb{Q}}\left(r_{t+m}\right) \\ =& c^{(m+1)} - c^{(m)} + \iota'\left(\phi^{\mathbb{Q}}\right)^m x_t. \end{aligned} \tag{16}$$

## 3.2 Long–Short Sensitivity in the Model

To connect this model to long–short sensitivity, consider one-period innovations in forward rates and yields. Denoting innovations with tildes, forward rate innovations are

$$\tilde{f}_t^{(m)} \equiv f_t^{(m)} - E_{t-1}\left(f_t^{(m)}\right) = \iota'\left(\phi^{\mathbb{Q}}\right)^m \epsilon_t. \tag{17}$$

Yield innovations are averages of forward rate innovations,

$$\begin{aligned} \tilde{y}^{(m)} \equiv& y_t^{(m)} - E_{t-1}\left(y_t^{(m)}\right) \\ =& \frac{1}{m}\sum_{i=0}^{(m-1)} \tilde{f}_t^{(i)} \\ =& \frac{1}{m}\left(I - \left(\phi^{\mathbb{Q}}\right)^m\right)\left(I - \phi^{\mathbb{Q}}\right)^{-1} \epsilon_t. \end{aligned} \tag{18}$$

Consider projecting the innovation in the $m_1$-maturity yield on the contemporaneous innovation in the $m_2$-maturity yield. The population regression coefficient is

$$\frac{\text{Cov}\left(\tilde{y}_t^{(m_1)}, \tilde{y}_t^{(m_2)}\right)}{\text{Var}\left(\tilde{y}_t^{(m_2)}\right)} = \frac{m_2}{m_1}\frac{\iota'\left(I - \left(\phi^{\mathbb{Q}}\right)^{m_1}\right)\left(I - \phi^{\mathbb{Q}}\right)^{-1}\Sigma\left(\left(I - \left(\phi^{\mathbb{Q}}\right)^{m_2}\right)\left(I - \phi^{\mathbb{Q}}\right)^{-1}\right)'\iota}{\iota'\left(I - \left(\phi^{\mathbb{Q}}\right)^{m_2}\right)\left(I - \phi^{\mathbb{Q}}\right)^{-1}\Sigma\left(\left(I - \left(\phi^{\mathbb{Q}}\right)^{m_2}\right)\left(I - \phi^{\mathbb{Q}}\right)^{-1}\right)'\iota}. \tag{19}$$

Equation (19) tells us that long–short sensitivity is determined by the eigenvalues of $\mathbb{Q}$ and the covariance matrix of the state innovations.

Straightforward intuition explains the roles of these parameters. To highlight the role of the eigenvalues, consider the special case of a one-dimensional state vector. Then $\phi^{\mathbb{Q}}$ is a scalar which we can think of as its eigenvalue $d$. In this case, (19) simplifies to

$$\text{One factor version:} \qquad \frac{\text{Cov}\left(\tilde{y}_t^{(m_1)}, \tilde{y}_t^{(m_2)}\right)}{\text{Var}\left(\tilde{y}_t^{(m_2)}\right)} = \frac{m_2}{m_1} \frac{(1 - d^{m_1})}{(1 - d^{m_2})}. \tag{20}$$

A long–short sensitivity regression corresponds to $m_2$ less than $m_1$. When $d$ is close to one, the state is highly persistent under $\mathbb{Q}$. Then short-term and long-term yields react similarly to an innovation. When $d$ is closer to zero, long-term yields react relatively less, resulting in a smaller long–short sensitivity.

The covariance matrix of state innovations affects long–short sensitivity in a multifactor setting. The simplest multifactor model has a state vector with independent elements, as in the two-factor version

$$\text{Two factor version:} \qquad \Sigma = \begin{pmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} \end{pmatrix}, \quad \phi^{\mathbb{Q}} = \text{diag}( \ d_1 \quad d_2 \ ),$$

$$\frac{\text{Cov}\left(\tilde{y}_t^{(m_1)}, \tilde{y}_t^{(m_2)}\right)}{\text{Var}\left(\tilde{y}_t^{(m_2)}\right)} = \frac{\frac{\left(1-d_1^{m_1}\right)\left(1-d_1^{m_2}\right)}{(1-d_1)^2}\Sigma_{11} + \frac{\left(1-d_2^{m_1}\right)\left(1-d_2^{m_2}\right)}{(1-d_2)^2}\Sigma_{22}}{\frac{\left(1-d_1^{m_2}\right)^2}{(1-d_1)^2}\Sigma_{11} + \frac{\left(1-d_2^{m_2}\right)^2}{(1-d_2)^2}\Sigma_{22}}. \tag{21}$$

The relative variances of the two factor innovations determine which eigenvalue plays a larger role in determining the long–short sensitivity. Section 3.4 presents a more general two-factor example in which the factor innovations are correlated.

## 3.3 Implications of Giacoletti, Laursen, and Singleton (2021)

Of course, the rolling regression estimates of Figure 1 imply that this constant-coefficient model is misspecified. Either $\mathbb{Q}$-persistence of the state vector, the covariance matrix of state-vector innovations, or both must vary over time. Evidence from the term structure literature casts considerable doubt on the importance of time-varying persistence. This evidence relies on the fact that $\mathbb{Q}$-persistence of the state can be inferred from the shape of the term structure.

Inspection of (15) reveals that the state affects yields through the state's $\mathbb{Q}$-persistence. Beginning with Chen and Scott (1993), the term structure literature recognizes that equations such as (15) can be inverted to infer an $n$-dimensional state vector from $n$ yields. Given $n$ yields, the remaining shape of the yield curve is determined by the model parameters. Therefore the cross-section of term structure shapes can be used to infer the state's $\mathbb{Q}$-persistence.

Giacoletti, Laursen, and Singleton (2021) produce rolling regression estimates of $\phi^{\mathbb{Q}}$ for a three-factor version of the model described here. For the period 1971 through 2014, they conclude that the matrix is "... virtually fixed over the entire sample..." (p. 409). A slightly more nuanced interpretation of their rolling estimates is that largest estimated eigenvalue is constant throughout the sample. The other two estimated eigenvalues exhibit no time trend from 1971 through the early 1990s. Around 1994, these two eigenvalues move slightly in opposite directions until the beginning of the global financial crisis in the fourth quarter of 2008.

The evidence of Giacoletti et al. (2021) casts substantial doubt on the possibility that variations in long–short sensitivity exhibited in Figure 1 can be attributed to variations in the state's $\mathbb{Q}$-persistence. Economic models designed to explain variations in long–short sensitivity should focus on variations in the conditional covariance matrix of factor innovations.

### 3.4 A Stylized Example of Fundamental Innovations

Empirical results in the next section motivate this two-factor example. Yields react to news about both inflation and real activity. Thus, we can think of innovation-specific long–short sensitivity; sensitivity associated with inflation news and sensitivity associated with real activity news. Overall long–short sensitivity is (roughly) a weighted average of these innovation-specific sensitivities.

If we apply the simple two-factor model of (21) to this setting, innovation-specific long–short sensitivity is fixed by the eigenvalues, while overall long–short sensitivity depends on the relative variances of inflation and real activity news. The more general example here illustrates how innovation-specific long–short sensitivity can depend on both eigenvalues and the covariance matrix of innovations.

News about inflation and real activity arrives at $t$. This news affects the term structure through a mapping from fundamental news to state-variable innovations,

$$\epsilon_t = H\xi_t, \qquad \xi_t \sim N(0, I_{2\times 2}), \tag{22}$$

where the first and second elements of the vector $\xi_t$ contain inflation and real activity news respectively. For simplicity, inflation and real activity news are uncorrelated. The covariance matrix of state-variable innovations in (10) and (11) is

$$\Sigma = HH'. \tag{23}$$

Pinning down the model requires specifying $H$ and the eigenvalues of$\phi^{\mathbb{Q}}$.

Consider two choices for $H$, labeled Case 1 and Case 2.

$$\text{Case 1:} \quad H = \begin{pmatrix} 1 & 0 \\ -0.5 & 1 \end{pmatrix}; \tag{24}$$

$$\text{Case 2:} \quad H = \begin{pmatrix} 1 & 0.8 \\ -0.5 & -0.3 \end{pmatrix}. \tag{25}$$

For both cases, the eigenvalues of $\phi^{\mathbb{Q}}$ are

$$\phi^{\mathbb{Q}} = \begin{pmatrix} 0.993 & 0 \\ 0 & 0.9 \end{pmatrix}. \tag{26}$$

Think of time as measured in months. From (13), the equivalent-martingale half-lives of two factors are a little more than eight years and a little more than six months.

Figure 3 summarizes the model's intuition with different choices of $H$. Consider the effect of fundamental news on current and $\mathbb{Q}$-expected future short rates. Revisions in the $i$-ahead $\mathbb{Q}$-forecast are

$$E_t^{\mathbb{Q}}(r_{t+i}) - E_{t-1}^{\mathbb{Q}}(r_{t+i}) = \begin{pmatrix} 1 & 1 \end{pmatrix} \left(\phi^{\mathbb{Q}}\right)^i H\xi_t. \tag{27}$$

Figure 3 plots these forecasts for one-unit innovations in inflation and real activity. The scaling of the figure is arbitrary because the units of inflation and real activity are not specified.

Cases 1 and 2 exhibit the same response of $\mathbb{Q}$-expected future short rates to positive inflation news. The blue lines show that the short rate immediately increases and is anticipated to continue to increase for roughly the next 18 months. The short rate is anticipated to slowly decline after about 18 months.

The response of $\mathbb{Q}$-expected future short rates to real activity news differs considerably between the two cases. With Case 1, the short rate immediately jumps, then is expected to quickly decline. This monotonic behavior is similar to the pattern observed with quartile 1 in Figure 2's Panel B. Innovations in $\mathbb{Q}$-expected future short rates are close to zero for horizons beyond three years. With Case 2, the immediate reaction of the short rate is much weaker than in Case 1. The short rate is anticipated to rise for a few years, then slowly decline. This nonmonotonic pattern is similar to the pattern observed with quartile 4 in Figure 2's Panel B.

Measure long–short sensitivity with the population coefficient for regressing changes in the seven-year yield on changes in the one-year yield. A news-specific sensitivity is defined as the coefficient when the other type of news is shut off. The inflation-specific and real activity-specific sensitivities for Case 1 are 1.05 and 0.20 respectively. The overall sensitivity is 0.64. The corresponding sensitivities for Case 2 are 1.05 (unchanged from Case 1), 0.97, and 0.99.

Case 2's greater $\mathbb{Q}$-persistence of short rates is attributable to greater $\mathbb{Q}$-persistence of real activity innovations. With Case 1, the model's lower eigenvalue entirely determines the reactions of forward rates to real activity news. With Case 2, both eigenvalues determine these reactions.

This highly stylized no-arbitrage model is open to various interpretations. There is no monetary authority nor a monetary policy function. Nonetheless, informally we might think of these two cases as roughly capturing active and passive monetary policy with respect to real activity. Other interpretations are possible. This example says nothing about risk premia since only the equivalent-martingale measure is modeled. We could add physical measure dynamics that would allow for greater (or less) variation over time in risk premia with Case 2 than with Case 1. But long–short sensitivity, by itself, says nothing about risk premia dynamics.

# 4 Exploring Economic Interpretations

This section investigates empirically whether the changes in the economic environment can explain the time-variation documented in Figure 1. To preview the results, the strongest evidence relates long–short sensitivity to the responsiveness of the one-year yield to real-side news, and the responsiveness of the seven-year yield to Fed funds surprises.

Recall the definition of conditional long–short sensitivity $S_t$ embedded in (4) and (5). Discussion in the previous section motivates the functional form

$$S_t = S(\Sigma_{t-1}), \tag{28}$$

where $\Sigma_t$ is the time-$t$ conditional covariance matrix of innovations to the canonical state vector that drives the term structure. Generalizing the example of Section 3.4, we can add a little economic content by writing the $n$-vector of innovations to canonical state variables in (22) as a function of fundamental economic news,

$$\underbrace{\epsilon_t}_{n\times 1} = \underbrace{H_{t-1}}_{n\times p}\underbrace{\xi_t}_{p\times 1}, \qquad \mathrm{Var}_{t-1}(\xi_t) = \Omega_{t-1}, \tag{29}$$

where $p$-dimensional economic news is in the vector $\xi_t$. Then the conditional covariance matrix of the canonical state vector is

$$\Sigma_t = H_t \Omega_t H_t'. \tag{30}$$

This setup leads to a functional form for long–short sensitivity of

$$S_t = \mathcal{S}(H_{t-1}, \Omega_{t-1}). \tag{31}$$

If we could observe fundamental economic news, we could infer $H_t$ period-by-period. We could also construct estimates of $\Omega_t$, and thus estimate the function (31). Unfortunately, substantial research fails to identify observable fundamental news that drives much of the innovations in bond yields. In other words, we know little about the elements of $\xi_t$ in (29).

More precisely, we observe types of macroeconomic news that clearly move bond prices. However, this news arrives infrequently. Kuttner (2001), Cochrane and Piazzesi (2002), and

Piazzesi (2005) conclude that yields across the term structure react strongly to monetary policy shocks identified with high-frequency data. Similarly, Gürkaynak, Sack, and Swanson (2005) show that the news components of many macroeconomic data releases are correlated with contemporaneous changes in bond yields. Yet monetary policy shocks are realized only once every six weeks or so. Swanson and Williams (2014) calculate that collectively, macroeconomic announcements explain, in an $R^2$ sense, less than 20% of the daily changes in bond yields.

I therefore adopt two less direct approaches to connect long–short sensitivity to economic fundamentals.

## 4.1 Conditional Long–Short Sensitivity Regressions

The approach here approximates the unknown function (31) with an affine function of observables that are plausibly connected to long–short sensitivity. Put differently, the observables are proxies for the unknown $\Omega_t$ and $H_t$.

Natural proxies for conditional volatilities of fundamental shocks (the unknown $\Omega_t$) are conditional volatilities of broad categories of observed macroeconomic and financial variables. The mapping from fundamental news to bond yields, captured by $H_t$, might depend on the state of the economy. Investors predict how the Fed will react to the fundamental news. Their predictions might differ across booms and recessions, or across normal and abnormal times. The mapping from fundamentals to yields might also depend on the level of short-term rates. Swanson and Williams (2014) use zero-bound logic to argue that the response of short-term rates is muted when these rates are particularly low, even if not at the lower bound.

A regression approach conditions long–short sensitivity on proxies for conditional volatility and conditional sensitivity. Write conditional sensitivity in (5) as

$$S_t = b'W_t, \tag{32}$$

where the vector $W_t$ contains conditioning information including a constant (normalized to one).

I include three broad measures of conditional volatility constructed by Jurado, Ludvigson, and Ng (2015). Their monthly indexes are averages, across a wide variety of time series, of square roots of forecast error variances. McCracken and Ng (2016) list all 279 time series. One set of indexes captures overall macroeconomic uncertainty and another captures financial uncertainty. Ludvigson, Ma, and Ng (2021) carve out "real" uncertainty from macroeconomic uncertainty by excluding time series related to money, credit, interest rates, exchange rates, price levels, and the stock market. The remaining time series relate to output, income, housing, the labor market, inventories, and business orders. The measures of volatility in $W_t$ are one-month-ahead measures of real uncertainty, overall macroeconomic uncertainty, and financial uncertainty for the calendar month prior to day $t$'s calendar month.[3]

My proxy for the state of the macroeconomy is the Brave-Butters-Kelley coincident index described by Brave, Butters, and Kelley (2019). The monthly index measures the deviation of economic growth from a long-term historical average. The absolute value of this index captures deviations from normal times. I use the one-year Treasury bond yield as a proxy for the level of short-term rates. The coincident index value for day $t$'s conditioning information is for the calendar month prior to day $t$'s calendar month. The one-year yield conditioning information for day $t$ is the yield as of day $t-1$.

Table I contains the results. On balance, the estimates do not support any relation that is both economically strong and consistent across the entire sample period. Over the full sample, only one coefficient is economically significant. A one standard deviation decrease in the real volatility index corresponds to an increase in the long–short regression coefficient of about 0.15. Underlying that inverse relation is the sharp break in real-side volatility associated with the Great Moderation beginning in the mid-1980s. Splitting the sample in half effectively throws away the information in the break. The table reveals that for both halves, the estimated coefficient on real volatility is positive, economically small, and statistically insignificant.

Two other full-sample parameter estimates are statistically significant, but that's a reflection of more than 11,000 observations rather than economic importance. For example, a one standard deviation decrease in the one-year yield raises the long–short regression coefficient by only 0.045. Moreover, the estimated coefficient switches sign between the first-half and second-half samples.

It is worth highlighting the strong positive relation between real activity and long–short sensitivity in the second half of the sample. As is well-known, real activity drops sharply

[3]Thanks to Sydney Ludvigson for maintaining these data on her website.

throughout 2001, peaks in the first half of 2004, and drops again throughout 2008. A glance at Figure 1 reveals the same pattern in rolling regression estimates of long–short sensitivity. However, the largest variation in real activity occurs during the 1970s and early 1980s, without any corresponding variation in long–short sensitivity.

## 4.2 Macroeconomic Announcements

Bond yields react to macroeconomic statistical releases. This section asks whether the magnitudes of these reactions vary with the level of overall long–short sensitivity. The model of Section 3.4 provides one motivation for this exercise (and also motivates the term "overall long–short sensitivity"). Changes in the reactions of yields to macroeconomic news produce changes in the covariance matrix of term structure factor innovations, which in turn produce changes in long–short sensitivity.

Another motivation turns this logic around. Instead of explaining long–short sensitivity using information from macroeconomic announcements, we can use long–short sensitivity to better understand how macroeconomic news affects the term structure. A decades-old, ever-growing literature builds dynamic macroeconomic models with term structure implications. The information in conditional long–short sensitivity can identify periods when reactions of yields to macroeconomic news are relatively strong and relatively weak.

Following an interest rate literature dating to at least Grossman (1981), we observe the news content of government statistical releases, defined as the announced values less forecasts from *Money Market Services*. For each news announcement, we also observe changes in bond yields from the end of the previous day through the end of the announcement day.

We do not observe directly long–short sensitivity. Thus I approximate it using a local regression. To fix ideas, consider a particular type of announcement $a$, say nonfarm payroll, with an announcement on day $\tau$. The estimate of long–short sensitivity for day $\tau$ uses daily changes in yields for the 40 trading days prior to $\tau$ and the 40 trading days after $\tau$, excluding all days in this range with the same type of announcement $a$. Using these observations, I regress changes in the seven-year yield on contemporaneous changes in the one-year yield. No constant term is included.

Denote this coefficient estimate for the day $\tau$ announcement as $\hat{S}_\tau$. Express the reaction of the $m$-maturity bond yield to the announcement as a function of this estimated long–short sensitivity,

$$\Delta y_{\tau}^{(m)} = b_{0,m}^{a} + b_{m}^{a}(\hat{S}_{\tau})\eta_{\tau}^{a} + e_{\tau,m}^{a}, \quad b_{m}^{a}(\hat{S}_{\tau}) \equiv \left( b_{1,m}^{a} + b_{2,m}^{a} \frac{\hat{S}_{\tau} - \overline{\hat{S}_{\tau}}}{SD(\hat{S}_{\tau})} \right). \tag{33}$$

In (33), $\eta_{\tau}^{a}$ is the news in announcement type $a$ on day $\tau$. This news is normalized to a mean-zero, unit standard deviation random variable.

Using (33), we can define announcement-specific long–short sensitivity; the expected response of the seven-year bond yield to the news relative to the expected response of the one-year bond yield to the news. This sensitivity is

$$\mathcal{S}^{a}(\hat{S}_{\tau}) = \frac{b_{7yr}^{a}(\hat{S}_{\tau})}{b_{1yr}^{a}(\hat{S}_{\tau})}. \tag{34}$$

There is no reason for this announcement-specific long–short sensitivity at $\tau$ to equal the overall long–short sensitivity at $\tau$. The latter averages across all types of news that drive bond yields.

I use eight types of announcements for which at least 200 months of announcement surprises are available. This set includes four announcements about inflation (CPI, core CPI, PPI, core PPI) and four announcements more closely related to the real economy (nonfarm payroll, retail sales excluding autos, durable goods orders, and initial unemployment claims). Initial unemployment claims are announced weekly. All other announcements are monthly. Announcement news for four of the series (CPI, PPI, nonfarm payroll, durable goods) begin in October 1985. Core CPI, Core PPI, and retail sales excluding autos begin in August 1989. Initial claims begins in July 1991. Regressions use data through September 2008.

Before discussing the results, two features of this 1985 through 2008 period are worth mentioning. First, as Figure 1 shows, rolling-regression estimates of long–short sensitivity average about one during this period. Second, as mentioned in Section 4.1, in this sample period there is a strong positive relation between real activity and long–short sensitivity. Since the sample from 1961 through 1984 does not exhibit this strong relation, it is possible that announcement-level results for 1985 and up are not informative about the entire sample.

Table II contains results. Estimates of regression (33) coefficients $b_{1,m}^{a}$ and $b_{2,m}^{a}$ are in the columns labeled “Surprise” and “Interaction” respectively. The table also reports estimates of announcement-specific long–short sensitivity (34). This sensitivity is estimated for both the mean value of $\hat{S}_\tau$ over the announcement sample and for a value of $\hat{S}_\tau$ that is one standard deviation greater than the mean. The table's final column tests whether the difference between these values is statistically significant. Generalized Method of Moments (GMM) standard errors for (34) incorporate uncertainty in both the seven-year and one-year regressions (33). None of the standard errors in the table account for sampling uncertainty in $\hat{S}_\tau$.

The table shows that variation in overall long–short sensitivity is a real-side phenomenon, and is unrelated to inflation news. Inflation announcement estimates are reported in Panel A. Estimates of $b^a_{1,m}$ in (33) are similar to those reported by Gürkaynak et al. (2005), although they examine somewhat different maturities. News of higher CPI and Core CPI raise one-year and seven-year yields, while new of higher Core PPI raises the seven-year yield. News about PPI does not significantly affect yields. The important result in Panel A is that responses of yields to inflation announcements do not vary with overall long–short sensitivity. Estimates $b^a_{2,m}$ are all economically insignificant and statistically indistinguishable from zero.

Real-side announcement estimates are reported in Panel B. Announcement types are ordered by the $R^2$ of (33) for the one-year yield. (The $R^2$ ordering is unchanged if the coefficient $b^a_{2,m}$ is fixed to zero.) Across all announcements, good news about real activity raises bond yields, although $R^2$s vary widely across announcement types. All estimates of $b^a_{1,m}$ are positive and statistically different from zero at the 5% critical value.[4]

A more important result for this paper is that when local overall long–short sensitivity is high, these real-side announcement surprises have smaller effects on the one-year yield than when local overall sensitivity is low. For example, when local overall sensitivity is one standard deviation higher than usual, the effect on the one-year yield of a unit SD nonfarm payroll surprise drops by 25%, from 1.9 bp to 1.5 bp. Statistical reliability of this inverse relation is greater for announcements more closely related to bond yields (nonfarm payroll, retail sales) or are observed more frequently (initial unemployment claims). Local overall sensitivity is less strongly related to the relation between announcement surprises and the seven-year yield. The "Interaction" estimates for the seven-year yield are all closer to zero than are the corresponding estimates for the one-year yield.

As a consequence of these patterns, higher overall long–short sensitivity corresponds to

[4] I reverse the sign of news of initial claims for unemployment.

higher announcement-specific long–short sensitivity. This conclusion is statistically reliable only for nonfarm payroll because the standard errors are considerably smaller than for other announcement types. The high $R^2$s of the nonfarm payroll regressions account for the low standard errors. Estimates in the columns labeled 'Mean' and 'Mean +1 SD' show that when local overall sensitivity is at its sample mean (1.07), estimated nonfarm payroll sensitivity is 0.92. When overall sensitivity is one standard deviation higher (1.32), estimated nonfarm payroll sensitivity is 1.15. Both retail sales ex autos and durable goods have larger estimated differences between the 'Mean' and 'Mean +1 SD' than does nonfarm payroll, although the standard errors are an order of magnitude larger for these announcements.

A final observation rounds out the discussion of Table II. Across Panels A and B, all but one of the 'Mean' values of announcement-specific long–short sensitivity are about 1.0, as is overall long–short sensitivity during the sample period spanned by these announcements. The exception is Core PPI, for which the standard error is extremely large.

This similarity suggests that a wide variety of types of macroeconomic news might have, on average, similar long–short sensitivity. Some types of news have large effects on yields (e.g., nonfarm payroll), and others have smaller effects (e.g., CPI). Yet across these macroeconomic announcements, the relative effects of news on one-year and seven-year bonds are similar. However, as we see in the next subsection, long–short sensitivity of monetary policy surprises differs considerably from long–short sensitivities documented in this subsection.

## 4.3 Monetary Policy Surprises

This section extends the macroeconomic announcement methodology to FOMC announcements. Two complications arise. First, monetary policy surprises are measured by unexpected changes in interest rates (e.g., the Fed funds target was unexpectedly increased), rather than by unexpected components of statistical releases (e.g., nonfarm payroll was 100,000 larger than expected). Second, monetary policy announcements are multidimensional, conveying information about both current and expected future levels of the Fed funds rate.

Swanson (2021) argues that FOMC policy surprises prior to 2009 can be decomposed into news about the current Fed funds rate and orthogonal news about $\mathbb{Q}$-expected future Fed funds rates during the next year (forward guidance). After 2008, FOMC announcements also contain news about large scale asset purchases (LSAP), but that news is irrelevant to the sample period studied here. Swanson constructs Fed funds news and forward guidance news as fixed-coefficient linear combinations of changes in Fed funds futures, Eurodollar futures, and Treasury bond yields in small time windows around FOMC announcements. I use his data. The sample contains 154 observations from July 1991 through September 2008.

Stack the two-dimensional monetary policy news for the FOMC announcement on day $\tau$ in the vector $\eta_\tau^f$, where "f" denotes FOMC. Swanson scales the news so that both types have a unit variance over the July 1991 through June 2019 sample. Regress one-day changes in yields on this news, allowing the regression coefficient to depend on the estimated overall long–short sensitivity on day $\tau$.

$$\Delta y_\tau^{(m)} = b_{0,m}^f + b_m^{f\,\prime}(\hat{S}_\tau)\eta_\tau^f + e_{\tau,m}^f, \quad b_m^f(\hat{S}_\tau) \equiv \left(b_{1,m}^f + b_{2,m}^f \frac{\hat{S}_\tau - \overline{\hat{S}_\tau}}{SD(\hat{S}_\tau)}\right). \tag{35}$$

Define surprise-specific long–short sensitivity following (34). Intuitively, this ratio measures the reaction of the seven-year bond to a Fed funds or forward guidance surprise relative to the reaction of the one-year bond to the same surprise. More broadly, define FOMC-specific long–short sensitivity. Since there are two components to the news vector, this FOMC-specific sensitivity depends on the covariance matrix of the news:

$$\mathcal{S}^f(\hat{S}_\tau) = \frac{b_{7yr}^{f\,\prime}(\hat{S}_\tau)\widehat{\mathrm{Var}}(\eta^f)b_{1yr}^f(\hat{S}_\tau)}{b_{1yr}^{f\,\prime}(\hat{S}_\tau)\widehat{\mathrm{Var}}(\eta^f)b_{1yr}^{mps}(\hat{S}_\tau)}. \tag{36}$$

The covariance matrix in (36) is the sample covariance of the data.

Recall that Section 4.2 shows the one-year yield reacts less to real-side news when overall long–short sensitivity is high. A similar relation is mechanically almost impossible with Fed funds surprises. No-arbitrage ties innovations in the one-year yield tightly to news of current and $\mathbb{Q}$-expected Fed fund rates over the next year. Any systematic variation of Fed funds announcements with bond yields will appear, if at all, at longer maturities.

Table III contains the estimation results. The presentation mirrors Table II. In Panel A, estimates of regression (35) coefficients $b_{1,m}^f$ and $b_{2,m}^f$ are in the columns labeled "Surprise" and "Interaction" respectively. The table also reports estimates of surprise-specific long–short sensitivity (34) at the mean value of $\hat{S}_\tau$ and a value of $\hat{S}_\tau$ that is one standard deviation greater than the mean. The panel's final column tests whether the difference between these values is statistically significant. Panel B reports estimates of (36) at the mean value of $\hat{S}_\tau$ and one standard deviation greater than the mean.

Panel A reveals that one-year and seven-year bond yields respond strongly to FOMC surprises to Fed funds and forward guidance. The estimated $b^f_{1,m}$ coefficients are overwhelmingly significant for both types of surprises and both yields. Similar evidence for different maturities is in Swanson (2021). Note the high $R^2$s relative to those in Table II. Since monetary policy news is defined directly in terms of high-frequency changes in interest rates around FOMC announcements, the explanatory power of this news for one-day changes in yields is inherently larger than for news defined as unexpected components of macroeconomic statistical announcements.

Estimates of $b^f_{2,m}$ reveal that the seven-year yield reacts more to the Fed funds surprise when overall long–short sensitivity is high. A one standard deviation positive Fed funds surprise raises the seven-year yield by 2.7 bp when overall long–short sensitivity is at its mean (for this sample, 1.08), and raises the yield by 4.5 bp when this sensitivity is one standard deviation above its mean (1.35). By contrast, the responses of one-year and seven-year yields to forward guidance surprises are insensitive to the level of overall long–short sensitivity.

In combination, these estimates imply that higher overall long–short sensitivity corresponds to higher Fed funds long–short sensitivity, but not forward guidance long–short sensitivity. Panel B aggregates across both types of FOMC surprises, thus the estimates in the panel are weighted averages of the results in Panel A.

Fed funds surprises are similar to real-activity surprises in the sense that their relative effects on yields vary with the overall level of long–short sensitivity. However, note that the announcement-specific long–short sensitivity for Fed funds is considerably smaller for Fed funds surprises than for any of macroeconomic announcements examined in Table II. Fed funds surprises are associated with much faster decay, under $\mathbb{Q}$, of short-rate innovations than are other surprises.

To summarize the announcement-level results, long–short sensitivity of real-side surprises and Fed funds surprises positively covaries with overall long–short sensitivity. It takes only a small leap to hypothesize that overall long–short sensitivity is *created* by time-varying long–short sensitivity of real-side news and news about the central bank's short-rate policy. We cannot test directly this hypothesis because we do not directly observe this news outside of well-defined announcements.

A large literature in macro-finance constructs dynamic models of macroeconomic news, monetary policy, and bond yields. Each parameterized model pins down long–short sensitivity, given specified long and short maturities. Models with regime shifts in monetary policy, such as in Campbell, Pflueger, and Viceira (2020), will produce variations over time in long–short sensitivity. However, although monetary policy is clearly characterized by changes in regimes over time, these changes do not line up cleanly with the time-variation in long–short sensitivity apparent in Figure 1.

Bae, Kim, and Kim (2012) use both narrative evidence and statistical tests to infer U.S. monetary policy regime changes from 1956 through 2005. They identify regimes with ending dates of 1968Q1, 1979Q4, 1985Q1, and 1997Q1. A glance at Figure 1 reveals that long–short sensitivity is moderately stable during only one of these periods (1985Q2 through 1997Q1). It varies widely during each of the other identified regimes.

Hanson et al. (2021) propose a risk-premium explanation for variations in long–short sensitivity. I take a close look at their conclusion in Section 5. In the next subsection I examine whether risk compensation is associated with long–short sensitivity over the 1961 through 2008 sample.

## 4.4 Expected Excess Returns

The persistence of short-rate innovations under the equivalent-martingale measure determines long–short sensitivity. Changes in $\mathbb{Q}$ dynamics associated with changes in long–short sensitivity are necessarily accompanied either accompanied by corresponding changes in physical dynamics and/or changes in the wedge between $\mathbb{Q}$ and physical dynamics. Changes in the wedge are equivalent to changes in risk premia dynamics.

This section asks empirically whether changes in either physical dynamics or risk premia are associated with changes in long–short sensitivity. In brief, the available evidence points to changes in physical dynamics rather than risk premia.

Mechanically, the yield on an $m$-maturity bond is the sum of mean expected future short rates and the expected log excess return to the bond over its life,

$$y_t^{(m)} = y_t^{(m)(P)} + y_t^{(m)(Q-P)}, \tag{37}$$

$$y_t^{(m)(P)} \equiv \frac{1}{m}\sum_{i=0}^{m-1} E_t\left(r_{t+i}\right), \qquad y_t^{(m)(Q-P)} \equiv y_t^{(m)} - y_t^{(m)(P)}. \tag{38}$$

If the expectations in (38) were observed, we could connect physical measure expectations to long–short sensitivity using rolling regressions. Simply replace the long-maturity yield change on the left side of (6) with the change in expected future short rates $y_t^{(m)(P)}$.

Since we do not observe expected future short rates, we can replace them with realizations. Applying monthly data to the sensitivity of the seven-year yield to one-year yield, a natural regression is

$$\frac{1}{m}\left[\left(\sum_{i=0}^{83}\left(r_{t+i}\right)\right) - \left(\sum_{i=0}^{83}\left(r_{t-1+i}\right)\right)\right] = b_0 + \left(b_1 + b_2\hat{S}_t\right)\Delta y_t^{(1yr)} + e_{t,t+83} \tag{39}$$

where $\hat{S}_t$ is an estimate of seven-year–one-year sensitivity for month $t$. However, the left side of (39) spans seven years. There are only seven non-overlapping observations in the sample studied here. Reliable statistical inference of (39) is impossible.

I therefore estimate a more informal version of (39),

$$r_{t+12} - r_{t-1} = b_0 + \left(b_1 + b_2 D_t\right)\Delta y_t^{(1yr)} + e_{t,t+12} \tag{40}$$

where $D_t$ is a dummy variable that equals zero if $t$ is prior to 1985 and one otherwise. We know from Figure 1 that long–short sensitivity is on average much higher when $D_t = 1$ than when $D_t = 0$. Therefore regression (40) tests whether a change in the one-year yield forecasts a larger change in the short rate over the next year when sensitivity is high than when sensitivity is low. One-month Treasury rates are taken from the CRSP Riskfree Rate file.

A qualitatively converse regression replaces the future change in the short rate on the left of (40) with the realized one-year excess return to the seven-year bond. The regression is

$$ex_{t,t+12}^{7yr} = b_0 + \left(b_1 + b_2 D_t\right)\Delta y_t^{(1yr)} + e_{t,t+12}, \tag{41}$$

where the excess return is defined as

$$ex^{7yr}_{t,t+12} \equiv 7y^{(7yr)}_t - 6y^{(6yr)}_{t+12} - \frac{1}{12}\sum_{i=0}^{11} r_{t+i}.$$

Regression (41) tests whether an increase in the one-year yield forecasts a higher excess long-term bond return over the next year through 1984 than from 1985 through 2008.

Table IV contains results. The first reported regression confirms what is obvious from Figure 1: long–short sensitivity is substantially lower in the 1961–1984 sample than in the 1985–2008 sample. A ten basis point monthly change in the one-year yield corresponds to an increase in the seven-year yield of about 5.0 bp and 8.5 bp respectively. The $p$-value of a Wald test of equality is less than 0.1%.

The second reported regression is (40). For the same 10 bp increase in the one-year yield, the early sample point estimate implies that the one-month rate increases by about 7 basis points over the 12 months. The late sample point estimate implies a much larger increase of more than 23 basis points. The hypothesis of equality is overwhelmingly rejected.

By contrast, future excess bond returns are statistically unrelated to the change in the one-year yield in both the early and late samples. In (41), the estimates of $b_1$ and $b_2$ indicate that higher long–short sensitivity is associated with *lower* sensitivity of risk premia to changes in the one-year yield rather than higher sensitivity. But the standard errors are large. Estimates of both $b_1$ and $b_2$ are statistically indistinguishable from zero and indistinguishable from each other.

# 5 Long–Short Sensitivity in the 21st Century

Data samples used in the previous sections end just prior to the onset of the global financial crisis. Hanson et al. (2021) examine long–short sensitivity during 2000 through 2019. They document and attempt to explain a surprising fact. During this period, estimates of long–short sensitivity decline substantially with the horizon over which changes in yields are measured. This horizon dependent pattern does not hold over the 1971 through 1999 period.

Hanson et al. (2021) argue that the inverse relation between the horizon and estimated long–short sensitivity reflects time-varying risk premia, perhaps due to limited capital. For concreteness, consider news at day $t$ that lowers current and expected future short rates.

Fixed-income arbitrageurs make money, raising their available capital and temporarily lowering their required risk premium on bonds. This decrease in risk premia puts additional downward pressure on longer-term yields, making them more responsive on day $t$ to the news than in the absence of the risk-premium effect. Over time, the extra capital shifts out of the fixed income space, causing longer-term yields to partially revert.

My view is that this pattern is less economically interesting than suggested by Hanson et al. (2021). Instead, is created by some sample-specific variation over time in long–short sensitivity.

## 5.1 Horizon Dependence

Table V reports estimates of long–short sensitivity for different horizons and sample periods. The bond's maturities are one and seven years. The first row of results confirms what we already know from Figure 1. Sensitivity is much lower in the first part of the sample. For the 1961 through 1989 period, estimates are a little above 0.5 for the daily, monthly, and quarterly horizons. The daily estimate is a little greater than the estimates for the other horizons, but all point estimates are statistically indistinguishable from 0.55. During the 1990s, long-term yields are much more sensitive to short-term yields than earlier. The estimates decline with horizon, from 1.0 (daily) to 0.8 (quarterly). That said, none of the estimates differ statistically from one at the 5% level.

As shown by Hanson et al. (2021), sensitivity declines strongly with horizon in the 2000 and later period. The daily coefficient is about one, while the hypothesis that sensitivity equals one is rejected at the 1% level for both monthly and quarterly horizons.

Yield dynamics during the 2000 and up period differ noticeably in other ways as well. Table VI reports the first three autocorrelations of monthly changes in yields for the sample periods considered in Table V. The striking result in the table is the sharp difference between the one-year and seven-year autocorrelations for the 2000 through 2022 period. The one-year yield is highly positively autocorrelated, while the seven-year yield is close to a martingale.

## 5.2 A broader view of the term structure

Figure 4 illustrates the source of these autocorrelations for 2000 through 2022. Two long-lived events dominate this sample: early 2000 through mid-2005 and October 2007 through

2017. During both events, shorter-term yields steadily declined over the course of two years, flattened out, and eventually steadily rose. During these same events, longer-term yields declined much less than shorter-term yields and bounced around. The only similar event during the 1961 through 1999 period occurred during the early 1990s, although the initial descent and subsequent rise in shorter-term yields both were much steeper than during the more recent events.

These patterns produce positive autocorrelation in one-year yields but not long-term yields. It is worth emphasizing that during both events, the steady decline in one-year yields was unanticipated. Traders in the one-year bond would have left substantial money on the table if at, say, month-end January 2001 (when the one-year yield had declined 120 basis points in two months) or month-end November 2007 (when the one-year yield had declined 80 basis points in a month) they expected the one-year yield to continue to decline precipitously.

Minutes from the FOMC provide narrative evidence. During a conference call in January 2001, the FOMC decided to reduce the Fed funds target from 6.5% to 6.0%. At its regular meeting on January 31 it reduced the target to 5.5%. The FOMC minutes refer to this reduction as an aggressive "front-loaded" easing policy: "...the stimulus provided by the Committee's policy easing actions would help guard against cumulative weakness in economic activity and would support the positive factors that seemed likely to promote recovery later in the year." At its meeting on December 11 2007, the FOMC lowered its target by 25 basis points. The minutes reveal uncertainty about whether future changes would be positive or negative. "Some members noted the risk of an unfavorable feedback loop in which credit market conditions restrained economic growth further, leading to additional tightening of credit; such an adverse development could require a substantial further easing of policy. Members also recognized that financial market conditions might improve more rapidly than members expected, in which case a reversal of some of the rate cuts might become appropriate."

## 5.3 Testing Possible Explanations

The lens of Hanson et al. (2021) provides a straightforward interpretation of the behavior of long-term yields during these events. As short rates begin to decline, long-term bond prices rise, building up arbitrageur capital and lowering the risk premium. Over time this capital flows out, partially reversing the initial decline in long-term yields. However, capital is replenished by the continued decline in short rates. We can test an empirical implication of this theory by regressing the change in the seven-year yield on the contemporaneous change in the one-year yield and the lagged multiperiod change in the one-year yield. The logic implies that the coefficient on the lagged change is negative, picking up the risk-premium reversal.

I test this hypothesis, as well as others, using the general regression implemented at the daily frequency

$$\Delta y_{t-1,t}^{(7yr)} = b_0 + b_t \Delta y_{t-t,t}^{(1yr)} + b_L \frac{1}{K} y_{t-1,t-K}^{(1yr)} + e_{t-1,t}. \tag{42}$$

The subscripts on changes in yields specify the dates over which the changes are measured. Different parametric assumptions for $b_t$ produce different regressions. The capital-flow explanation corresponds to the case of

$$\text{Case 1}: \qquad b_t = b_1. \tag{43}$$

With this case, the one-day change in the seven-year yield is regressed on the contemporaneous change in the one-year yield and the average of the past $K$ day change in the one-year yield.

Panel A of Table VII reports tests of (43) using $K = 40$ days. Results are not substantially different when using $K = 20$ or $K = 60$. The table presents results for three separate samples. The coefficient on the lagged change in the one-year yield is negative and statistically significant for all three. As suggested by the evidence of Hanson et al. (2021), the estimate is much larger (in absolute value) for the 2000 through 2022 period than for either 1961 through 1989 or 1990 through 1999.

This evidence supports the limited capital explanation. However, an alternative explanation for the large negative coefficient in 2000 through 2022 does not rely on arbitrageurs or capital flows. With this alternative, (43) is misspecified. The two large events during the 21st century were characterized by a specific type of conditional long–short sensitivity. When the Federal funds rate began to decline at the beginning of these events (before they were "events"), investors anticipated these changes would be highly persistent. Thus longer-term yields reacted strongly. As the funds rate continued to decline investors interpreted these subsequent changes in funds rate as less persistent. Expressed differently, investors became more confident the bottom was near when rates were cut further. Therefore $b_t$ in (42) declined as rates dropped during 2001–2002 and from October 2007 through 2008.

This is a sample-specific explanation, not a statement of the population properties of yields. Figure 3 of Cieslak (2018) supports this explanation. The figure displays the time path of the Fed funds rate along with monthly Blue Chip forecasts of future Fed funds rates. The forecast horizons range from the nowcast to four quarters ahead. First consider the 2000 through 2005 period. As the funds rate began its decline in 2000 from 6%, forecasts of future rates were declining with the forecast horizon. When the funds rate reached 4%, forecasts were flat across horizons rather than declining. When the funds rate reached 2%, forecasts were increasing with the forecast horizon. Forecasts continued to increase in the horizon as the rate fell to 1%. The figure tells a similar story beginning in late 2007, although the zero lower bound makes the story somewhat mechanical. When the funds rate is at its lower bound, forecasts necessarily cannot decline.

Reconsider (42) from this explanation's perspective. As rates continue to fall at the beginning of these two events, the fixed-coefficient version (43) overestimates the decline in the seven-year yield as the one-year yield declines. Including the lagged change in the one-year yield helps correct this overestimate. A negative coefficient on this lagged change pushes the fitted change in the seven-year yield higher, consistent with the data.

This explanation and the one of Hanson et al. (2021) are not mutually exclusive. To distinguish their effects, I choose two ad hoc parametric forms for the conditional variation in the contemporaneous regression coefficient $b_t$ in (42). Define an indicator variable that equals one if the current change in the one-year yield is in the same direction as the recent trend in the one-year yield. The variable is

$$\mathcal{I}_t = \begin{cases} 1, & \Delta y_{t-1,t}^{(1yr)} \Delta y_{t-K,t-1}^{(1yr)} > 0; \\ 0, & \text{otherwise.} \end{cases} \tag{44}$$

The simplest way to introduce conditional long–short sensitivity into (42) is

$$\text{Case 2}: \qquad b_t = b_1 + b_2 \mathcal{I}_t. \tag{45}$$

With this case, long–short sensitivity equals $b_1 + b_2$ if the current change is in the same direction as the change over the previous $K$ periods and $b_1$ otherwise. A version that better reflects the evidence in Cieslak's figure has long-short sensitivity depend on the magnitude of the lagged change,

$$\text{Case 3}: \qquad b_t = b_1 + b_2|\Delta y^{(1yr)}_{t-K,t-1}|\mathcal{I}_t. \tag{46}$$

Panels B and C of Table VII reports regression results for cases (45) and (46) respectively, using $K = 40$ days. Results are similar for choices of $K = 20$ or $K = 60$. The results convey three clear messages. First, the 2000 through 2022 sample exhibits economically and statistically strong conditional long–short sensitivity. From Panel B, the estimated coefficient conditioned on reversing direction (the indicator (44) is 0) is 1.18, and is 0.89 conditioned on continuing in the same direction. The estimates of long–short sensitivity from Panel C exhibits much more variation. Figure 5 displays the fitted values of (46). Although the mean fitted value is about 1.1, conditional sensitivity drops below 0.4 at points during 2001 and 2008.

Second, the two earlier samples exhibit no evidence of such conditional sensitivity. All of the relevant $t$-statistics are less than one in absolute value. This contrast is consistent with the dominant role played by the two large events during the 2000 through 2022 sample. Third, the lagged change in the one-year yield does not predict reversals in the seven-year yield during the 2000 through 2022 sample. The point estimates for both (45) and (46) are positive. The hypothesis that the coefficient is zero cannot be rejected at the 10% level for either case.

From a bird's eye view, Table VII tells the same story that begins with Figure 1 and continues through the macroeconomic regression evidence of Section 4. Long–short sensitivity varies widely over time. Unfortunately, Table VII also shares a limitation with this other evidence: the absence of clear economic explanations that are consistent with this evidence.

# 6 Concluding Remarks

This paper presents a combination of surprising and disappointing evidence. The sensitivity of long-maturity Treasury yields to changes in short-maturity Treasury yields varies surprisingly widely over time. A twenty-year trend towards increasing sensitivity ends in the mid-1980s with a coefficient of about one. The coefficient subsequently varies between 0.5

and 1.5. Although potential explanations are abundant, attempts to link this time-variation to underlying economic drivers are disappointingly largely unsuccessful.

The strongest evidence indicates that variations in long–short sensitivity are connected to real-side news and monetary policy shocks rather than inflation news. Whether the nature of the real-side news changes over time, or instead whether anticipated monetary policy reactions to the news changes over time, is not pinned down here.

The behavior of long–short sensitivity during 2000 and later period is particularly unusual. It is highly sensitive to recent changes in yields. When yields change on day $t$ in the same direction that they've changed over the past couple of months, long–short sensitivity is considerably lower than it is when the changes in yields are in the opposite direction. Economic explanations for this unusual behavior must await future research.

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**Table I**
**Conditional Regressions of Changes in the Seven-Year Yield on Changes in the One-Year Yield, June 1961–September 2008**

Daily changes in the seven-year Treasury yield are regressed on contemporaneous daily changes in the one-year Treasury yield

$$\Delta y_t^{7yr} = b_0 + \left(\sum b_i \left(explanatory\ var_i\right)\right) \Delta y_t^{(1yr)} + e_t$$

Explanatory variables are a constant, monthly measures of one-month-ahead conditional volatility from Jurado et al. (2015) and Ludvigson et al. (2021), a monthly measure of the deviation of economic growth from trend, the absolute value of this deviation, and the one-year bond yield. The constant is normalized to one. The other explanatory variables are normalized to mean-zero, unit variance variables. Asymptotic standard errors are in parentheses. They are adjusted for generalized heteroskedasticity. Asterisks represent two-sided $p$-values at the 10%, 5%, and 1% significance levels.

| Explanatory Variables | 6/1961–8/2008 11,786 Obs. | 6/1961–12/1984 5,866 Obs. | 1/1985–9/2008 5,920 Obs. |
|---|---|---|---|
| Constant | 0.765*** | 0.508*** | 1.000*** |
| | (0.014) | (0.031) | (0.026) |
| Real Volatility | −0.154*** | 0.035 | 0.012 |
| | (0.022) | (0.035) | (0.044) |
| Macro Volatility | 0.023 | −0.054* | −0.027 |
| | (0.020) | (0.032) | (0.042) |
| Financial Volatility | −0.020 | −0.049* | 0.021 |
| | (0.021) | (0.026) | (0.020) |
| Real Activity Gap | 0.009 | 0.001 | 0.152*** |
| | (0.019) | (0.023) | (0.030) |
| Abs(Real Activity Gap) | 0.041** | 0.004 | 0.005 |
| | (0.018) | (0.018) | (0.025) |
| One Year Yield | −0.045*** | 0.058** | −0.038 |
| | (0.014) | (0.028) | (0.023) |

## Table II
## Responses of Yields to Macroeconomic Announcement News

This table report estimates of Equation (33) in the text. One-day changes in one-year and seven-year Treasury yields are regressed on the surprise component of the specified macroeconomic announcement and an interaction term. The interaction term is the product of the surprise and a rolling-sample estimate of the sensitivity of daily changes in seven-year yields to daily changes in one-year yields. Macroeconomic announcement surprises are standardized to mean-zero, unit-variance variables. The rolling-sample estimate is also normalized to a mean-zero, unit-variance variable. Yields are measured in annualized basis points.

Announcement specific long–short yield sensitivity is defined by Equation (34) in the text. It is evaluated at two values of the rolling-sample sensitivity: the sample mean and one standard deviation above the sample mean. Asymptotic standard errors, adjusted for generalized heteroskedasticity, are in parentheses. Asterisks represent two-sided $p$-values at the 10%, 5%, and 1% significance levels.

Panel A. Inflation Announcements

| | | One-Year Yield | | | Seven-Year Yield | | | Announcement-Specific Long–Short Sensitivity | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Announcement | Num of Obs | Surprise | Interaction | $R^2$ | Surprise | Interaction | $R^2$ | Mean | Mean +1 SD | Difference |
| CPI | 276 | 0.384*** | 0.047 | 0.03 | 0.395** | 0.018 | 0.03 | 1.03*** | 0.96*** | −0.07 |
| | | (0.112) | (0.108) | | (0.160) | (0.164) | | (0.23) | (0.32) | (0.23) |
| Core CPI | 230 | 0.640*** | 0.043 | 0.10 | 0.702*** | 0.018 | 0.09 | 1.10*** | 1.05*** | −0.04 |
| | | (0.123) | (0.108) | | (0.159) | (0.145) | | (0.13) | (0.20) | (0.12) |
| PPI | 276 | 0.114 | −0.144 | 0.01 | 0.134 | −0.119 | 0.01 | 1.18* | −0.50 | −1.67 |
| | | (0.114) | (0.124) | | (0.140) | (0.138) | | (0.69) | (8.12) | (8.43) |
| Core PPI | 230 | 0.116 | −0.033 | 0.00 | 0.298*** | −0.130 | 0.03 | 2.56* | 2.01 | −0.54 |
| | | (0.105) | (0.077) | | (0.116) | (0.092) | | (1.60) | (1.46) | (1.35) |

Panel B. Real Activity Announcements

| | | One-Year Yield | | | Seven-Year Yield | | | Announcement-Specific Long–Short Sensitivity | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Announcement | Num of Obs | Surprise | Interaction | $R^2$ | Surprise | Interaction | $R^2$ | Mean | Mean +1 SD | Difference |
| Nonfarm Payroll | 276 | 1.909*** | −0.441*** | 0.33 | 1.746*** | −0.061 | 0.23 | 0.92*** | 1.15*** | 0.23*** |
| | | (0.159) | (0.136) | | (0.207) | (0.185) | | (0.07) | (0.11) | (0.08) |
| Retail Sales | 229 | 0.526*** | −0.420*** | 0.12 | 0.503*** | −0.311* | 0.06 | 0.96*** | 1.81 | 0.85 |
| Ex Autos | | (0.103) | (0.107) | | (0.154) | (0.169) | | (0.16) | (1.17) | (1.10) |
| Durable Goods | 273 | 0.431*** | −0.152 | 0.06 | 0.508*** | 0.044 | 0.05 | 1.18*** | 1.98*** | 0.80 |
| | | (0.147) | (0.147) | | (0.165) | (0.165) | | (0.18) | (0.70) | (0.66) |
| (Neg of) Initial | 880 | 0.644*** | −0.326** | 0.05 | 0.680*** | −0.321** | 0.03 | 1.06*** | 1.13*** | 0.07 |
| Unempl Ins Claims | | (0.127) | (0.151) | | (0.145) | (0.153) | | (0.13) | (0.36) | (0.30) |

**Table III**

**Responses of Yields to Monetary Policy Shocks**

This table report estimates of Equation (35) in the text. One-day changes in one-year and seven-year Treasury yields are regressed on the surprise components of Fed funds and forward guidance information in FOMC announcements. Regressions include interaction terms, which are the product of a surprise component and a rolling-sample estimate of the sensitivity of daily changes in seven-year yields to daily changes in one-year yields. FOMC surprises, normalized to unit standard deviations, are from Swanson (2021). The rolling-sample estimate is also normalized to a mean-zero, unit-variance variable. Yields are measured in annualized basis points.

Announcement specific long–short yield sensitivity is defined by Equation (34) in the text. FOMC announcement long–short sensitivity across both types of surprises is defined by Equation (36). Both equations are evaluated at two values of the rolling-sample sensitivity: the sample mean and one standard deviation above the sample mean. Asymptotic standard errors, adjusted for generalized heteroskedasticity, are in parentheses. Asterisks represent two-sided $p$-values at the 10%, 5%, and 1% significance levels. There are 154 observations from July 5 1991 through Sept 16 2008.

Panel A. Regression Estimates

| Type of Surprise | One-Year Yield | | Seven-Year Yield | | Surprise-Specific Long–Short Sensitivity | | |
|---|---|---|---|---|---|---|---|
| | Surprise | Interaction | Surprise | Interaction | Mean | Mean +1 SD | Difference |
| Fed funds | 5.111*** | 1.006 | 2.672*** | 1.801** | 0.523*** | 0.731*** | 0.208** |
| | (1.113) | (0.794) | (0.906) | (0.852) | (0.091) | (0.123) | (0.086) |
| Forward guidance | 2.785*** | 0.436 | 3.039*** | 0.539 | 1.091*** | 1.111*** | 0.020 |
| | (0.759) | (0.619) | (0.661) | (0.627) | (0.146) | (0.101) | (0.123) |
| $R^2$ | 0.451 | | 0.298 | | | | |

Panel B. FOMC Announcement Long–Short Sensitivity

| Value of Overall Long–Short Sensitivity | | |
|---|---|---|
| Sample Mean | Sample Mean Plus One Std Dev | Difference |
| 0.66*** | 0.82*** | 0.16*** |
| (0.07) | (0.07) | (0.06) |

**Table IV**
**Regressions of Changes in Yields and Excess Bond Returns on the Change in the One-Year Yield, July 1961 through September 2008**

The explanatory variable in all regressions is the change in the one-year Treasury yield from the end of month $t-1$ to the end of month $t$. The first column lists the dependent variables. The regressions are estimated over the entire data sample, allowing the coefficient for $t$ prior to 1985 to differ from the coefficient for $t$ after 1984. Asymptotic Newey-West standard errors are in parentheses. The lag length is 1.25 times the number of overlapping observations (which is zero for the first regression). The final column lists a two-sided $p$-value for a test of the hypothesis that the coefficients are equal across the early and late samples. One, two, and three asterisks represent two-sided $p$-values at the 10%, 5%, and 1% significance levels.

| Dependent | 1961:7–1984:12 | | 1985:1–2008:9 | | | Test of |
|---|---|---|---|---|---|---|
| Variable | Obs | Coef | Obs | Coef | $R^2$ | Equality |
| Contemporaneous Change in 7 Year Treasury Yield | 282 | 0.480*** (0.034) | 285 | 0.843*** (0.046) | 0.67 | 0.000 |
| Change in 1 Month Bill Rate from Month $t-1$ to Month $t+12$ | 282 | 0.731*** (0.180) | 273 | 2.383*** (0.477) | 0.08 | 0.001 |
| Log Excess Return to 7 Year Bond from Month $t$ to Month $t+12$ | 282 | −0.794 (0.932) | 273 | −1.592 (1.980) | 0.00 | 0.712 |

**Table V**
**Long–Short Sensitivity for Different Horizons and Periods**

The table reports coefficients from univariate regressions of changes in the seven-year Treasury yield on contemporaneous changes in the one-year Treasury yield. Changes are measured over successive days, months, or quarters. Regressions for monthly and quarterly horizons use non-overlapping observations. Asymptotic standard errors, adjusted for generalized heteroskedasticity, are in parentheses. The number of observations is in brackets.

| Sample | Daily | Monthly | Quarterly |
|---|---|---|---|
| June 15 1961–Dec 29 1989 | 0.57 | 0.51 | 0.52 |
| | (0.02) | (0.04) | (0.05) |
| | [7114] | [342] | [114] |
| Jan 3 1990–Dec 31 1999 | 1.01 | 0.92 | 0.82 |
| | (0.04) | (0.08) | (0.11) |
| | [2482] | [119] | [39] |
| Jan 4 2000–Dec 30 2022 | 1.01 | 0.78 | 0.68 |
| | (0.03) | (0.08) | (0.07) |
| | [5752] | [275] | [91] |

**Table VI**
**Autocorrelations of Monthly Changes in Yields**

$$\Delta y_t^{(m)} = b_i^{(m)} + \rho_i^{(m)} \Delta y_{t-i}^{(m)} + e_{t,i}^{(m)}$$

The table reports $\rho_i^{(m)}$ from these univariate regressions of monthly changes in Treasury yields on lagged monthly changes of the same yield. Standard errors, adjusted for generalized heteroskedasticity, are in parentheses. One, two, and three asterisks represent two-sided $p$-values versus zero at the 10%, 5%, and 1% significance levels.

| | One Year Yield | | | Seven Year Yield | | |
|---|---|---|---|---|---|---|
| Sample | $i = 1$ | $i = 2$ | $i = 3$ | $i = 1$ | $i = 2$ | $i = 3$ |
| 1961:6–1989:12 | 0.14 | $-0.12$ | $-0.08$ | 0.07 | $-0.08$ | $-0.07$ |
| (Obs = 342 - $i$) | (0.09) | (0.11) | (0.08) | (0.08) | (0.08) | (0.08) |
| 1990:1–1999:12 | 0.37*** | 0.10 | 0.07 | 0.19* | 0.00 | 0.01 |
| (Obs = 119 - $i$) | (0.10) | (0.11) | (0.10) | (0.10) | (0.07) | (0.10) |
| 2000:1–2022:12 | 0.36*** | 0.38*** | 0.23** | 0.06 | $-0.13$* | 0.07 |
| (Obs = 275 - $i$) | (0.07) | (0.09) | (0.10) | (0.07) | (0.07) | (0.06) |

**Table VII**
**Daily Changes in the 7-Year Yield**
**Regressed on Contemporaneous and Lagged Changes in the 1-Year Yield**

The table reports OLS estimates of one-day changes on the seven-year yield on contemporaneous and the 40-day lagged change in the one-year yield,

$$\Delta y_{t-1,t}^{(7yr)} = b_0 + b_t \Delta y_{t-t,t}^{(1yr)} + b_L \left( \frac{1}{40} y_{t-1,t-40}^{(1yr)} \right) + e_{t-1,t},$$

for different parametric choices of $b_t$ described in the text. Yields are measured in annualized percent. Standard errors, adjusted for generalized heteroskedasticity, are in parentheses. One, two, and three asterisks represent two-sided $p$-values versus zero at the 10%, 5%, and 1% significance levels.

| Sample | Constant Term for $b_t$ | Conditional Term for $b_t$ | $b_L$ |
|---|---|---|---|
| Panel A: Constant $b_t$ | | | |
| June 1961–December 1989 | 0.578*** | | −0.131*** |
| (7,074 obs) | (0.019) | | (0.051) |
| Jan 1990–December 1999 | 1.010*** | | −0.236*** |
| (2,442 obs) | (0.035) | | (0.092) |
| Jan 2000–December 2022 | 1.018*** | | −0.372*** |
| (5,712 obs) | (0.027) | | (0.083) |
| Panel B: Include Dummy for Same Sign of Current, Lagged Change in 1 Yr | | | |
| June 1961–December 1989 | 0.569*** | 0.017 | −0.149** |
| | (0.035) | (0.048) | (0.065) |
| Jan 1990–December 1999 | 0.981*** | 0.055 | −0.311** |
| | (0.078) | (0.100) | (0.148) |
| Jan 2000–December 2022 | 1.180*** | −0.286*** | 0.031 |
| | (0.045) | (0.066) | (0.117) |
| Panel C: Dummy is Multiplied by Absolute Lagged Change in 1 Yr | | | |
| June 1961–December 1989 | 0.567*** | 0.017 | −0.170*** |
| | (0.023) | (0.019) | (0.058) |
| Jan 1990–December 1999 | 1.045*** | −0.166 | −0.104 |
| | (0.057) | (0.163) | (0.135) |
| Jan 2000–December 2022 | 1.159*** | −0.529*** | 0.169 |
| | (0.031) | (0.078) | (0.105) |

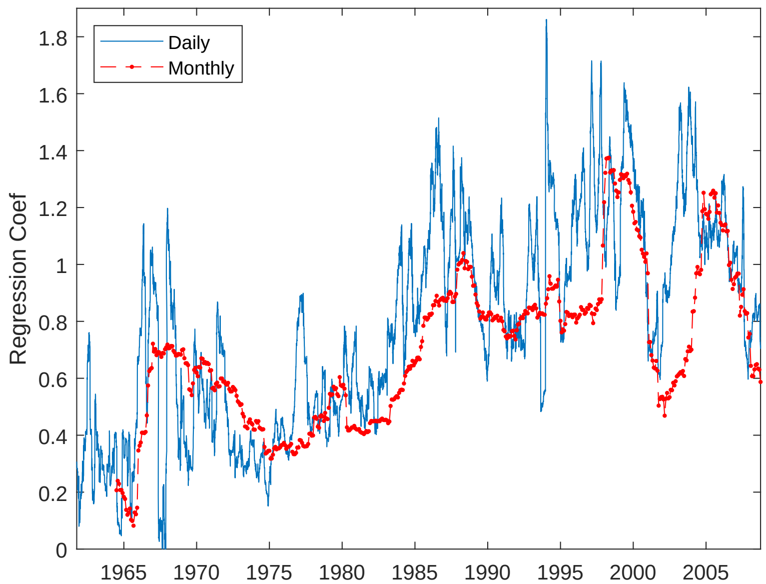


Figure 1. Coefficients from regressions of changes in the seven-year Treasury yield on contemporaneous changes in the one-year Treasury yield. Regressions of daily changes use rolling samples of 80 trading days. Regressions of monthly changes use rolling samples of 36 months.

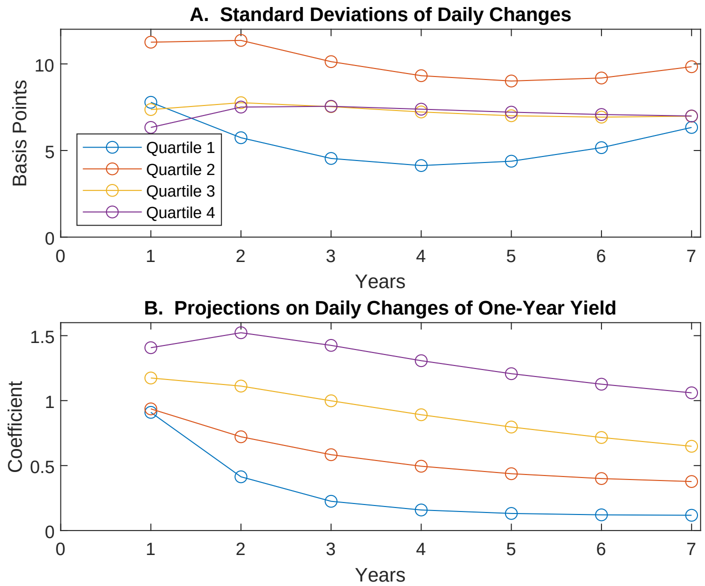


Figure 2. Properties of instantaneous forward rates. All quarters from 1961Q2 through 2008Q3 are sorted into four equal-sized groups using quarterly estimates of long–short sensitivity, as described in the text. Quarters in the first (fourth) quartile have the lowest (highest) estimated long–short sensitivity. Panel A displays, for each group, standard deviations of daily changes in instantaneous forward rates. The forward-rate horizons are one to seven years. Panel B displays, for each group, estimates of regressions of daily changes in the forward rates on contemporaneous daily changes in the one-year Treasury yield.

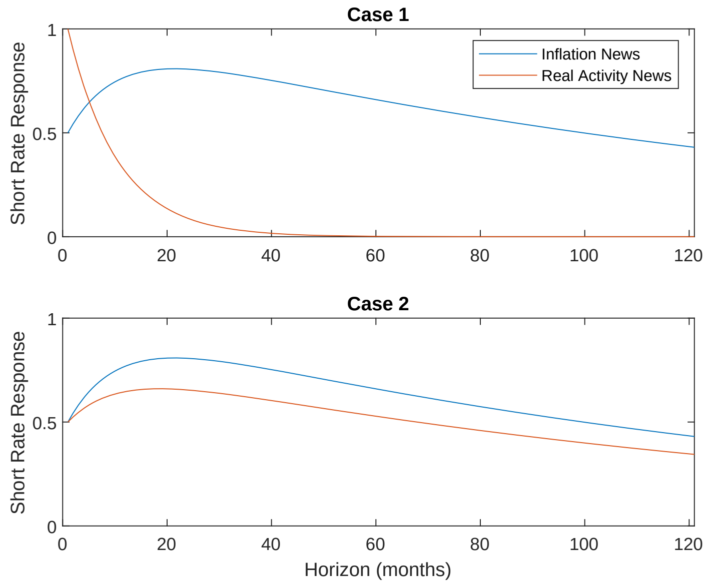


Figure 3. Properties of a stylized no-arbitrage term structure model. Inflation and real activity news at $t$ alter the equivalent-martingale expected short rate at $t+i$ months ahead. The figure displays $i$-ahead innovations for two different model parameterizations.

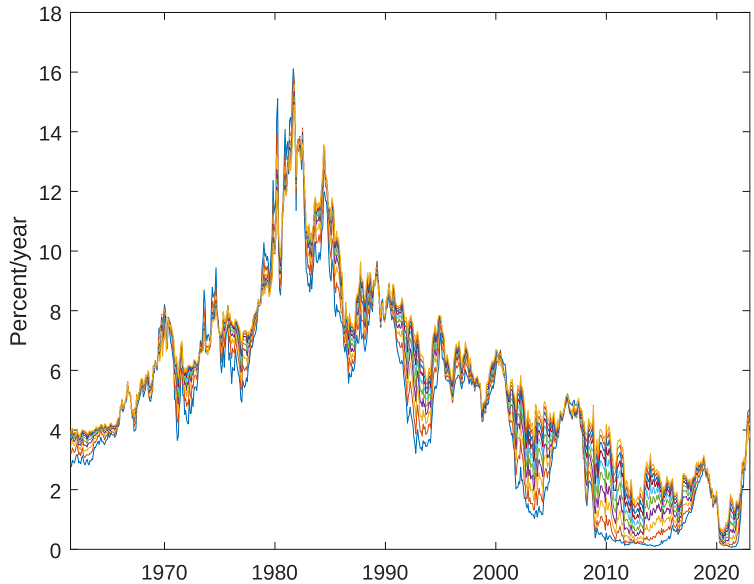


Figure 4. Month-end yields on zero-coupon Treasury bonds with maturities from one to ten years. Observations prior to September 1971 include maturities only through seven years. Gürkaynak et al. (2007) interpolate these yields from prices of traded Treasury bonds.

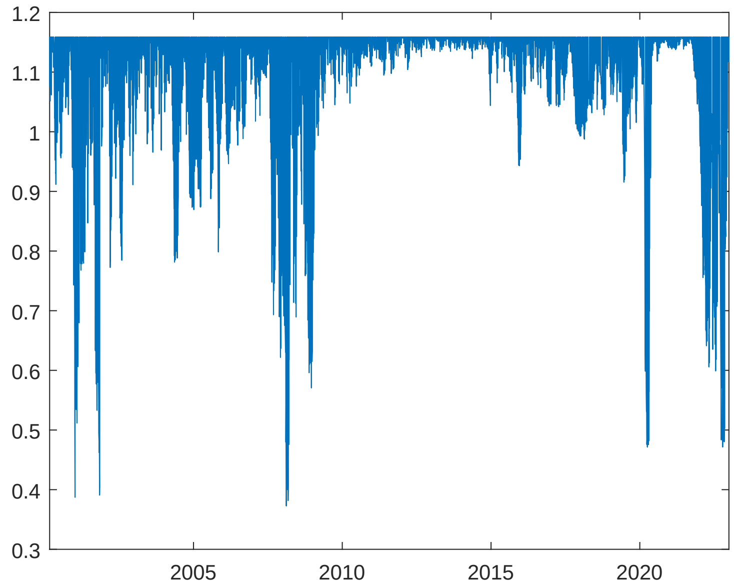


Figure 5. Regression estimates of the sensitivity of daily changes in the seven-year Treasury yield to the contemporaneous change in the one-year Treasury yield. The specification of conditional sensitivity is described by (46) in the text. The sample is 2000 through 2022.