What Do Yield Spread Trades Tell Us about Economic Activities and Asset Prices?

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ABSTRACT

Using positions data on bond futures, I document that yield spread trades contain predictive information about economic activities and asset prices. Steepening trades are associated with higher subsequent recession probabilities and lower subsequent payroll growths. In particular, speculators have a superior ability to form payroll expectations as their steepening trades precede negative payroll surprises. Furthermore, speculators' steepening trades predict variations in the yield curve and pre-FOMC stock returns, suggesting that the pre-FOMC puzzle can be explained by trading in anticipation of easing policies. Overall, speculators' spread trades can be useful as a leading economic indicator as they contain information about future economic activity and monetary policy.

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Economic fundamentals and monetary policy are primary drivers of asset returns. Do sophisticated investors have a superior ability to form expectations on future economic activity and monetary policy? This topic is an age-old question in finance and yet timely as professional investors have increasingly used data-crunching technologies and alternative data sources, such as satellite images, traffic data, internet search data, social media data, and credit card transactions. Academics have caught up with the trend by adopting machine learning methods in macroeconomic and return forecasting.[1]

I conjecture that superior macroeconomic expectations may manifest themselves into investors' yield spread trades—a purchase of one bond future and a simultaneous sale of another bond future with a different maturity. The conjecture is motivated by the stylized fact that the slope of the yield curve has a close relationship to economic activity and monetary policy.[2] Given such relationship, curve-steepening trades can be useful right before or during a recession in which short-term rates tend to drop faster than long-term rates. Curve-flattening trades can be useful during a monetary tightening in which short-term rates tend to rise faster than long-term rates. Therefore, informed investors' spread trading, if identified, can be a good candidate as a leading economic indicator which aggregates the market's heterogeneous information about future economic activity and monetary policy.

In addition to the close link to economic activity and monetary policy, spread trading has two appealing features for informed trading, compared to outright trading: low cost and low risk. Spread trading requires a smaller margin than outright trading, facilitating informed traders to take higher leverage. Black (1975) and Easley, O'Hara, and Srinivas (1998) show that leverage is a crucial determinant of informed trading. Moreover, spread trading is viewed as a low-risk strategy because it is largely shielded from a parallel shift

[1] For example, Henderson, Storeygard, and Weil (2012) show that satellite images on night lights can be useful for measuring economic growth when traditional data are of low quality or unavailable. Gu, Kelly, and Xiu (2020) and Bianchi, Büchner, and Tamoni (2020), among others, show that machine learning methods can be useful for predicting asset returns by capturing the non-linearity.

[2] See Diebold, Rudebusch, and Aruoba (2006), Gürkaynak, Sack, and Swanson (2005), and Rudebusch and Wu (2008). In addition, Harvey (1988), Estrella and Hardouvelis (1991), and Estrella and Mishkin (1998), among others, find that the inverted yield curve is a good predictor of upcoming recessions.

in the term structure of interest rates. Duration-matched spread trading, in particular, can be useful when investors are informed about economic activity but uncertain about more permanent shocks, such as inflation shock, which tend to affect yields more evenly across all maturities.

A casual observation suggests that large speculators in bond futures may have played the slope of the yield curve in the right direction. Figure 1 shows the excess net number of large speculators in bond futures using the Commitments-of-Traders (COT) report published by the Commodity Futures Trading Commission. With the average net number of speculators removed, the excess net number is intended to measure abnormal trading activity in short-term bond markets relative to long-term ones. The figure shows remarkable divergences in abnormal trading activity between Eurodollar futures and 30-year Treasury futures during all of the recessions, including the recent coronavirus recession. In particular, speculators took a bullish (bearish) view on short-term (long-term) bond markets relative to long-term (short-term) bond markets during all of the recession periods. Such empirical regularity provides preliminary evidence that large speculators in bond futures may have superior information about future economic activities and monetary policy.

Having observing the empirical pattern above, I introduce spreading indicators that mimic speculators' spread trading, with the expectation that they distill information dispersed across various investors. Indeed, the spreading indicators have predictive power for future economic activity. Probit regression analysis shows that speculators' stronger steepening (flattening) is associated with a higher (lower) probability of subsequent recessions. In addition, stronger steepening (flattening) is associated with lower (higher) non-farm payroll growth rates in subsequent months. The predictive power of the spreading indicators cannot be spanned by other business-cycle indicators such as term spreads and bond excess premiums as introduced by Gilchrist and Zakrajšek (2012).

To understand the source of the predictive power of spreading indicators, I compare speculators' ability to forecast future payrolls to that of professional forecasters.[3] I find that strong steepening (flattening) is associated with negative (positive) payroll surprises in subsequent months, suggesting that spread traders hold some information that is not accounted for by professional forecasters. Furthermore, spreading indicators can forecast asset markets' intraday response to future payroll announcements. Specifically, strong steepening is followed by positive returns on bond futures and depreciations of the U.S. dollar against major foreign currencies at the times of future payroll releases. Overall, I argue that speculators have a superior ability to analyze future payrolls and that such information manifests itself into their betting on the slope of the yield curve.

I also show that the information in spread trades can explain the otherwise puzzling pre-Federal Open Market Committee (FOMC) stock drift, the fact that a large fraction of excess stock returns have materialized during a few trading hours immediately preceding scheduled FOMC announcements (see Lucca and Moench 2015). Specifically, I find that speculators' stronger steepening is followed by greater stock drifts during trading hours between 9:30 a.m. on the FOMC announcement day and 15 minutes before the announcement. An active pre-FOMC timing strategy conditioned on the information in steepening trades would have delivered a Sharpe ratio gain of 0.36 relative to a naive pre-FOMC buy-and-sell strategy. Overall, information held by speculators has been incorporated into stock prices through pre-FOMC same-day trading.

Why is it that steepening trades are positively (but not negatively) associated with future pre-FOMC stock returns? The positive relationship is at first surprising because steepening trades are related to low economic activity, which may signal low corporate earnings in the future. However, stock markets sometimes interpret economic news upside down if the news is expected to affect the future course of monetary policy. In light of the positive relationship, speculators with bad news appear to have anticipated an easing policy and have

[3] Among various macroeconomic announcements, payrolls are known as "the king of announcements" (see Andersen and Bollerslev 1998).

engaged in informed trading just a few hours before the FOMC announcements. That is, the policy anticipation channel appears to be dominant relative to the non-monetary information channel during pre-FOMC same-day trading hours. This interpretation is consistent with empirical research showing that stock prices tend to increase following easing policies (see Rigobon and Sack 2004; and Bernanke and Kuttner 2005).

In a nutshell, I argue that speculators' spread trading contains unique information about future economic activity and the future direction of monetary policy. To further support such argument, I show that current spreading indicators can predict variations in the Treasury yield curve in following months. Specifically, strong steepening is followed by a reduction in short-term yields and an increase in the slope of the yield curve in subsequent months. The directions are consistent with the finding that current strong steepening is associated with lower economic activity and higher expectations of an easing policy into the future.

Related literature: This paper contributes to the finance and macroeconomic literature in three ways. First, there is a vast literature identifying business-cycle indicators from financial markets. For example, Harvey (1988), Estrella and Hardouvelis (1991), and Estrella and Mishkin (1998) find that the slope of the yield curve is a harbinger of recessions; Gilchrist and Zakrajšek (2012) document that credit spreads are a leading indicator of the business cycle; and Ang, Piazzesi, and Wei (2006) argue that short-term rates are more informative about gross domestic product (GDP) growth than term spreads. While this line of research typically focuses on asset prices to study macroeconomic expectations, I show that informed traders' strategies and positions can carry macroeconomic information which can help policymakers and practitioners understand the future state of the economy.

Second, this paper contributes to the literature documenting biases in professional forecasts. Coibion and Gorodnichenko (2012, 2015) provide a methodology for imputing consensus forecast errors to information rigidities. Andrade and Le Bihan (2013) relate the predictability of forecast errors to agents' inattention to new information. Campbell and Sharpe (2009) and Bordalo, Gennaioli, Ma, and Shleifer (2018) provide behavioral explanations for forecast biases. Froot and Frankel (1989) and Bacchetta, Mertens, and Van Wincoop (2009) document the empirical relationship between the predictability of excess returns and forecast errors. My paper provides new evidence that forecast biases can arise from forecasters' limited capacity to process macroeconomic information relative to some sophisticated investors.

Third, my findings have an implication for the literature studying asset returns on days of macroeconomic announcements or during a few hours before macroeconomic announcements. Following Lucca and Moench (2015), Cieslak, Morse, and Vissing-Jorgensen (2019) find a cyclical pattern of stock returns over the FOMC cycle. Kurov, Sancetta, Strasser, and Wolfe (2019) discover pre-announcement drifts before several macroeconomic announcements. Savor and Wilson (2013) find that stock returns and Sharpe ratios are higher on days of major macroeconomic announcements. Mueller, Tahbaz-Salehi, and Vedolin (2017) find that the U.S. dollar tends to depreciate relative to other currencies on days of scheduled FOMC announcements. Ai and Bansal (2018) develop revealed preference theory for macroeconomic announcement premiums. My paper contributes to this literature as it shows that macroeconomic announcement returns and pre-announcement drifts may be explained by speculators' strategic informed trading.

The rest of the paper is organized as follows: Section 1 introduces spread trading in bond futures, examines speculators' spread trading behavior, and defines spreading indicators; Section 2 examines the predictive power of spread trading for economic activity; Section 3 provides an explanation for the pre-FOMC stock drift using the information contained in spread trading; Section 4 examines the predictive power of spread trading for the yield curve; Section 5 discusses the policy implications of my findings; and Section 6 concludes.

1 Spread trading as a leading economic indicator

1.1 Motivation

Spread trading, in a more general form, refers to a purchase of one security and a sale of another related security. Sophisticated investors often engage in such a package deal in order to construct a portfolio that is most sensitive to the information they have. For example, suppose that you have a good ability to forecast whether a Category-five hurricane will hit the Gulf of Mexico. Given such an ability, you might consider taking a direct position in the West Texas Intermediate (WTI) crude oil futures, but the position would expose you to the risks that have little to do with the hurricane, such as political uncertainty in the Middle East. Instead, spread trading between the WTI and Brent crude oil futures just before the arrival of a hurricane would allow you to purely bet on the hurricane risk, eliminating other risks that are common to both oil prices.

I conjecture that the market's information about economic activity and monetary policy may manifest itself into spread trading in bond futures. This conjecture is based on the stylized macroeconomic fact that the slope of the yield curve is closely linked to real economic activity (see Diebold, Rudebusch, and Aruoba 2006). Figure 2 illustrates the tight relationship between the non-farm payroll growth rate and the slope factor in the Treasury yield curve, where the slope factor is the second principal component of a cross-section of Treasury yields with maturities of 1 to 30 years. Furthermore, the slope sharply responds to monetary policy shocks (see Gürkaynak, Sack, and Swanson 2005; Rigobon and Sack 2004; and Rudebusch and Wu 2008). For example, a policy rate cut is typically accompanied by a further steepening of the yield curve.

Given the stylized facts above, investors may profit from playing the slope of the yield curve if informed about future economic activity and monetary policy. For example, increasing holdings of short-term bonds relative to long-term bonds (curve steepening) can be useful right before or during a recession and a monetary easing. Conversely, reducing holdings of short-term bonds relative to long-term bonds (curve flattening) can be useful ahead of a monetary tightening. A zero-duration spread trade, in particular, can be useful when investors are uncertain about permanent shocks, such as inflation and productivity shocks, which tend to affect yields more evenly across all maturities.

In addition, the existing literature shows that leverage is an important factor in informed trading (see Black 1975; and Easley, O'Hara, and Srinivas 1998). While required margins are already very small for bond futures, spread trading requires an even smaller margin than outright trading. For example, in March 2018, margins were set at \$1,600 for ten-year Treasury futures and \$3,100 for 30-year Treasury futures. Meanwhile, the Chicago Mercantile Exchange allows for a 70% margin credit for a three-to-two-ratio spread trade between ten- and 30-year Treasury futures. Under this margin setting, a purchase of three ten-year Treasury futures and a sale of two 30-year Treasury futures would require margins of \$4,800 and \$6,200, respectively, but their combined trade would require a margin of only \$2,840.[4] Note that the margin for spread trading is much smaller than that for each of the two legs. Ultimately, low margins on spread trading would help informed traders lever their informational advantage.

Overall, the market's information about economic activity and monetary policy can be revealed through spread trading in bond futures. Admittedly, the slope of the yield curve is affected by many other factors such as inflation expectations and Treasury demand/supply shocks. For example, when inflation expectations pick up, the curve can steepen as long-term rates rise faster than short-term rates, which is called a "bear steepener." For another example, if incoming data suggest a further deepening of the recession that the economy has already been in, the curve can flatten because of safe-haven demand or reach-for-yield demand for long-term Treasury bonds, which is called a "bull flattener." Furthermore, in the past decade, central banks have increasingly relied on forward guidance and quantitative

[4] $\$6,200 - 0.7 \times \$4,800 = \$2,840$.

easing, and the non-conventional monetary policies may have different implications for the slope of the yield curve than conventional ones. Nevertheless, other factors generally have less of an influence on the slope of the yield curve than expectations on economic activities.

1.2 Data and stylized facts

To identify yield spread trading, I make use of the legacy (futures-only) COT data over the period from July 1986 to June 2020.[5] The data set contains information on the number of traders who are short and long for each futures contract, broken down into three investor groups: commercial, non-commercial, and non-reportable. The first two groups are considered to be large hedgers and speculators, whereas the last group represents small players whose open interest levels are below a certain threshold level. The data are released every other Friday until September 1992 and every Friday thereafter.

I particularly use the data on the net number of speculators (the difference between the numbers of long and short speculators) in the most liquid bond futures: Eurodollar (ticker=ED), ten-year Treasury (TY), and 30-year Treasury (US).[6] An issue in using the net number of speculators is that it is driven by not only spread trading but also outright trading, so the net number itself is not ideal for capturing speculators' view on the slope of the yield curve.

Instead, I introduce the excess net number of speculators as follows. Let SP_t^i denote the net number of speculators for a future contract $i \in \{3M, 10Y, 30Y\}$ at time t, where $3M$, $10Y$, and $30Y$ refer to Eurodollar futures, ten-year Treasury futures, and 30-year Treasury futures, respectively. I compute an equally-weighted average of the net speculators over the three selected futures: $\overline{\mathrm{SP}}_t = \frac{1}{3}\sum_{i\in\{3M,10Y,30Y\}} \mathrm{SP}_t^i$. The excess net number of speculators in

[5] The futures-and-options-combined data have a shorter time-series span than the futures-only data.

[6] I do not use two-year (TU) and five-year (FV) Treasury futures because the COT data on these bond futures are unavailable in the beginning of the sample period. In addition, as Eurodollar futures have maturities up to ten years, their term structure information overlaps that of two- and five-year Treasury futures. Similarly, I do not include federal funds futures because their trading volume is still one-order-of-magnitude smaller than that of Eurodollar futures.

each futures market is obtained by subtracting the average net number of speculators from the market's net number:

$$\mathrm{EXSP}_t^i = \mathrm{SP}_t^i - \overline{\mathrm{SP}}_t, \tag{1}$$

where EXSP_t^i denotes the excess net number of speculators for a future contract i at time t. With the average net number of speculators across different maturities removed, the excess net number is intended to measure abnormal trading activity in each futures market. For example, a positive value of EXSP_t^{3M} means that speculators are expecting Eurodollar futures to outperform the other bond futures overall.

Figure 1 shows the excess net number of speculators in Eurodollar futures (the solid line) and 30-year Treasury futures (the dotted line). The shaded areas refer to the four National Bureau of Economic Research (NBER)-designated recessions included in my sample period. The figure shows several stylized facts associated with speculators' bond trading behavior over business cycles. Specifically, the excess net number of speculators in Eurodollar futures began to rise before the start of all the recessions and stayed at positive levels throughout the recession periods, including the one associated with the coronavirus pandemic. In contrast, the excess net number of speculators in 30-year Treasury futures began to fall before the start of all the recessions and stayed at negative levels during all of the recession periods. That is, throughout the recession periods, speculators took a bullish (bearish) view on short-term (long-term) bond markets relative to long-term (short-term) ones. Importantly, the slope trading pattern started even before the onset of recessions, suggesting that speculators might have had information associated with the slope of the yield curve before the economy turned around.

1.3 Introducing spreading indicators

Let me introduce two indicators that mimic speculators' spread trading behavior. Recall that the excess net numbers of speculators show severe heteroskedasticity over time; that is, they have fewer fluctuations in the earlier part of the sample than in the later part of the sample. To account for such heteroskedasticity, I introduce a steepening indicator based on the signs of the excess net numbers. Specifically, I define a binary variable that equals one if the excess net number is positive in Eurodollar futures and negative in 30-year Treasury futures and zero otherwise. The steepening indicator is then defined as a quarterly moving average of the binary variable:

$$\text{STEEP}_t \equiv \frac{1}{N_t} \sum_{t-q<\tau\leq t} \mathbb{1}_{\text{EXSP}_\tau^{3M}>0} \mathbb{1}_{\text{EXSP}_\tau^{30Y}<0}, \tag{2}$$

where STEEP_t denotes the steepening indicator at time t, q stands for a quarter, and N_t denotes the number of observations over the past quarter.[7] A high value of STEEP_t is associated with speculators' expectations that the yield curve will become steeper in subsequent periods.

Similarly, I introduce another binary variable that equals one if the excess net number is negative in Eurodollar futures and positive in 30-year Treasury futures and zero otherwise. A flattening indicator is then defined as a quarterly moving average of the binary variable:

$$\text{FLAT}_t \equiv \frac{1}{N_t} \sum_{t-q<\tau\leq t} \mathbb{1}_{\text{EXSP}_\tau^{3M}<0} \mathbb{1}_{\text{EXSP}_\tau^{30Y}>0}, \tag{3}$$

where FLAT_t denotes the flattening indicator at time t. A high value of FLAT_t is associated with speculators' expectations that the yield curve will become flatter in subsequent periods.

The top panel of Figure 3 shows the time-evolution of the steepening indicator, where the shaded areas refer to the five easing episodes included in my sample period. Note that the steepening indicator stood at very high levels during most of the easing periods, except for the very brief easing period beginning in September 1998. Furthermore, the steepening

[7] Treasury futures mature only in the March quarterly cycle (March, June, September, and December). Eurodollar futures have four monthly series in addition to the March quarterly series, but a majority of the trading volume concentrates on the quarterly series. Therefore, taking a quarterly moving average on weekly (and fortnightly) positions data helps to remove the periodicity that can arise from the expiration and creation of futures contracts, which has nothing to do with informed trading.

indicator reached its peaks before the start of the two easing cycles that began in January 2001 and September 2007.

The bottom panel of Figure 3 shows the time-evolution of the flattening indicator, where the shaded areas refer to the five tightening episodes included in my sample period. While the flattening indicator was not turned on as frequently as the steepening indicator, speculators appear to have expected a further flattening of the yield curve during the three tightening episodes that started in February 1994, June 2004, and December 2015. In particular, speculators turned to the strongest flattening view after former Chairman Ben Bernanke first indicated a slowdown of quantitative easing in May 2013, a bond market turmoil called the taper tantrum.

Table 1 provides the summary statistics of the spreading indicators and their correlations with other business-cycle variables. Term spreads (TMSP) are defined as quarterly moving averages of the yield spreads between ten-year Treasury bonds and three-month Treasury bills; bond excess premiums (EBP) are a measure of credit risk premiums provided by Gilchrist and Zakrajšek (2012); and real federal fund rates (FFR) are defined as the differences between the effective federal fund rates and the inflation rates as implied by the core PCE (personal consumer expenditures) price index. An interesting feature emerging from the table is that both STEEP and FLAT are little correlated with TMSP. Similarly, correlations of STEEP and FLAT with EBP are modest at 0.36 and -0.25, respectively. Overall, the low-to-moderate correlations imply that spreading indicators may have very different information from TMSP and EBP.

2 Information content for economic activities

This section studies the predictive power of speculators' spread trading for future economic activities. I also discuss the private nature of the information contained in spread trading and compare the predictive power of spread trading to that of outright trading in various futures markets.

2.1 Forecasting recession probabilities

I start by looking at whether spreading indicators have predictive information about recession probabilities because the slope of the yield curve is known as a harbinger of recessions. Let SPRD_t denote a spreading indicator, which refers to either STEEP_t or FLAT_t. I then estimate a Probit regression model for h-month-ahead recession probabilities as follows:

$$Prob(rec_{t+h} = 1) = \Phi(\alpha + \beta\text{SPRD}_t + \gamma' z_t), \tag{4}$$

where rec_{t+h} denotes a dummy variable that equals one if month $t + h$ is declared to be a recession month and zero otherwise and z_t denotes a vector of control variables such as TMSP, EBP, and FFR.

Panel A of Table 2 shows in-sample Probit regression results. The panel shows that a higher value of STEEP is associated with a higher probability of recession in subsequent months up to one year. The statistical significance of STEEP is obtained at the 1% level for every forecast horizon considered. A higher value of FLAT is associated with a lower probability of recession in subsequent months. The statistical significance of FLAT is obtained at the 1% or 5% level. Note that these results survive the inclusion of control variables, suggesting that the spreading indicators contain distinct information about future recession probabilities from traditional predictors.

To assess out-of-sample forecasting power, I divide the entire sample period into two subperiods: the first in-sample estimation period (July 1986 to December 1999) and the out-of-sample evaluation period (January 2000 to June 2020). Here, I am interested in measuring the incremental forecasting power of spreading indicators beyond the well-known predictors. An out-of-sample R^2 measure is obtained by comparing the model as in Equation

(4) to the nested benchmark model without the spreading indicator as follows:

$$R^2 = 100 \times \left(1 - \frac{\sum_{t=T_b}^{T_e} rec_t \log(\widehat{p}_t) + (1 - rec_t)\log(1 - \widehat{p}_t)}{\sum_{t=T_b}^{T_e} rec_t \log(\widehat{p}_t^0) + (1 - rec_t)\log(1 - \widehat{p}_t^0)}\right), \tag{5}$$

where T_b and T_e denote the beginning and end of the out-of-sample evaluation period, respectively; $\widehat{p}_t^0$ denotes the recession probability forecast associated with the benchmark model excluding the spreading indicator; and $\widehat{p}_t$ denotes the recession probability forecast associated with the larger model including the spreading indicator. The statistical significance of the larger model against the benchmark model is evaluated using the McCracken (2007) test. The models are recursively estimated in each month throughout the out-of-sample evaluation period. I calculate an average of the coefficients on the spreading indicator over the out-of-sample evaluation period in order to see its effect on recession probabilities.

Panel A of Table 3 shows out-of-sample forecasting results, including out-of-sample R^2s, test statistics, and average coefficients ($\overline{\beta}$) on spreading indicators. The panel shows that STEEP has incremental forecasting power beyond term spreads with an R^2 of 30.0% (3 months ahead) or 24.8% (6 months ahead); and beyond bond excess premiums with an R^2 of 15.9% (3 months ahead) or 8.3% (6 months ahead). The panel also shows that FLAT has incremental forecasting power beyond term spreads with an R^2 of 17.2% (3 months ahead) or 14.1% (6 months ahead); and beyond bond excess premiums with an R^2 of 7.3% (3 months ahead) or 3.5% (6 months ahead). All the results are statistically significant at the 1% or 5% level.

Panel A of Table 3 also shows the out-of-sample performance measures during recessions (R^2_{Rec}) and expansions (R^2_{Exp}). The steepening indicator sometimes yields false detections of recessions during expansionary periods with $R^2_{Exp} < 0$. This result arises because speculators tend to maintain steepening positions in the recovery periods immediately following recessions, as can be seen in Figure 1. For example, while the 2001 recession came to an end in November 2001, speculators still maintained a strong steepening view in the following couple of years or so.

2.2 Forecasting non-farm payroll growth rates

I next examine the predictive power of spreading indicators for non-farm payroll growth rates by running the following h-month-ahead predictive linear regression:

$$g_{t+h} = \alpha + \beta \mathrm{SPRD}_t + \gamma' z_t + \delta g_t + \varepsilon_{t+h}, \tag{6}$$

where g_{t+h} denotes the monthly payroll growth rate between month $t+h-1$ and $t+h$ and ε_{t+h} is a forecasting error. The first-release vintage data are used to avoid a look-ahead bias (the results would be stronger with the revised data).[8] The sample period here spans from July 1986 to March 2020. Note that I drop the recent three observations (April through June 2020) relative to the case of recession forecasting.[9]

Panel B of Table 2 shows in-sample prediction results. The coefficient on STEEP is negative, implying that a higher value of STEEP is associated with a lower payroll growth rate in subsequent months. The statistical significance of STEEP is obtained at the 1% level for every forecast horizon. The coefficient on FLAT is positive, implying that a higher value of FLAT is associated with a higher payroll growth rate in subsequent months, with statistical significance at the 1% level for every forecast horizon. Note that the forecasting power of the spreading indicators survives the inclusion of the control variables, suggesting that the predictive information in spreading indicators is not subsumed by that in other variables.

[8] The vintage data are available at the Federal Reserve Bank of Philadelphia, `https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/data-files/employ`.

[9] There is an econometric issue in including the most recent payroll data (April through June 2020). Payrolls dropped by 20.5 million in April; and rose by 2.5 million in May and by 4.8 million in June. These changes are so astronomical that they have a critical influence on regressions. To put their sizes into perspective, the smallest change (2.5 million) over the past three months is 3.4 times larger than the maximum change (0.73 million) between November 1964 and March 2020.

To assess out-of-sample forecasting power, I compare the full model as in Equation (6) to the nested benchmark model without the spreading indicator. Specifically, an out-of-sample R^2 measure is defined as

$$R^2 = 100 \times \left(1 - \frac{\sum_{t=T_b}^{T_e}(g_t - \widehat{g}_t)^2}{\sum_{t=T_b}^{T_e}(g_t - \widehat{g}_t^0)^2}\right), \tag{7}$$

where $\widehat{g}_t$ and $\widehat{g}_t^0$ denote the forecast associated with the full and benchmark models, respectively. The entire sample period is divided two subperiods: the first in-sample estimation period (July 1986 to December 1999) and the out-of-sample evaluation period (January 2000 to March 2020). As before, the first-release vintage data are used.

Panel B of Table 3 shows out-of-sample forecasting results for non-farm payroll growth rates. STEEP has incremental forecasting power beyond term spreads with an R^2 of 14.4% (3 months ahead) or 16.8% (6 months ahead); and beyond bond excess premiums with an R^2 of 8.9% (3 months ahead) or 12.6% (6 months ahead). The results are statistically significant at the 1% level in every case. Similarly, FLAT has incremental forecasting power beyond term spreads with an R^2 of 4.5% (3 months ahead) or 5.4% (6 months ahead); and beyond bond excess premiums with an R^2 of 1.2% (3 months ahead) or 3.0% (6 months ahead). The forecasting power of the spreading indicators varies along phases of the business cycle. In particular, STEEP has greater forecasting power during recessions than during expansions, while R^2_{Rec} and R^2_{Exp} are both positive.

Given that a futures market has a zero net supply, one may wonder who took the opposite positions from speculators. To help understand this question, I repeat a similar analysis for the other two groups: large hedgers and small players. The result shows that small players' spreading indicators have predictive power for payroll growth rates with an opposite sign, whereas large hedgers' spreading indicators have no predictive power. Therefore, small players appear to have met the net demand from large speculators. The result is further discussed in Appendix A.1.

To summarize, speculators' spreading indicators have the predictive power for future economic activity particularly during recessions. The state dependence is aligned with the literature suggesting that economic agents tend to process macroeconomic information more actively during recessions than during expansions. For example, Kacperczyk, Nieuwerburgh, and Veldkamp (2014) show that professional managers are good at market timing particularly in bad times. Coibion and Gorodnichenko (2015) provide evidence that forecasters update macroeconomic information more frequently in bad times than in good times. Peng, Xiong, and Bollerslev (2007) argue that investors tend to shift limited attention to market-wide information following an increase in uncertainty.

2.3 Evidence of private information

One may argue that the forecasting power of spreading indicators does not necessarily mean that speculators have private information about economic activity. It is possible that speculators' superior ability to play the slope of the yield curve is based on macro-financial variables that have causal effects on economic activity; for example, term spreads and credit spreads may influence the real economy by affecting banks' net interest margins and firms' cost of funding, respectively. To reduce such endogeneity concern, I compare the forecasting ability of speculators to that of professional forecasters in two ways.

Predicting payroll surprises: I first show that speculators have information that is not impounded into payroll forecasts by running the following regression:

$$\mathrm{NFP}_{t+h} = \alpha + \beta \widetilde{\mathrm{NFP}}_{t+h} + \gamma \mathrm{SPRD}_t + \eta' z_t + \varepsilon_{t+h}, \tag{8}$$

where NFP_{t+h} and $\widetilde{\mathrm{NFP}}_{t+h}$ denote the first-release payroll number and the consensus forecast for month $t+h$, respectively. The consensus forecast data come from Action Economics from December 1987 to December 1996 and Bloomberg from January 1997 to March 2020.[10]

[10] I exclude the recent three-month period (April through June 2020) as in the forecasting of payroll growth rates.

In the regression as in Equation (8), the information between month t and $t+h$ is visible to professional forecasters but not to speculators in bond futures. If forecasters are fully informed and rational, β should be 1 and the other coefficients 0. I am particularly interested in testing the significance of the coefficient on SPRD_t, γ, to see whether professional forecasters miss out on some important information held by speculators.

Table 4 shows the regression results. Panel A of the table shows that the steepening indicator contains valuable information about future payrolls beyond consensus forecasts, although the statistical significance varies over forecast horizons. The coefficient on STEEP_t is negative, implying that strong steepening is associated with a negative payroll surprise in subsequent months. Panel B shows that the flattening indicator also has some information beyond consensus forecasts four to six months ahead, with statistical significance at the 5% level. The coefficient on FLAT_t is positive, implying that strong flattening is associated with a positive payroll surprise in subsequent months.

Unlike the spreading indicators, term spreads and bond excess premiums have no predictive power. Overall, spreading indicators have unique information about future payrolls that is not accounted for by professional forecasters.

Predicting intraday asset returns: I next show that spreading indicators can predict asset returns over intraday windows surrounding future payroll release times. To do so, I run the following predictive regression:

$$\mathrm{r}_{t+h}^{w_-,w_+} = \alpha + \beta \text{SPRD}_t + \eta' z_t + \varepsilon_{t+h}, \tag{9}$$

where $\mathrm{r}_{t+h}^{w_-,w_+}$ denotes the return on a futures contract over the intraday window starting w_- minutes before the payroll release time and ending w_+ minutes after. The intraday returns data come from Refinitiv Tick History, and the explanatory variables are observed h months before the intraday returns are realized. The sample spans from June 1996 to June 2020.

Table 5 shows the predictive power of spreading indicators for the three-month-ahead

($h = 3$) intraday returns with two choices of windows: $w_{-} = 5$ and $w_{+} = 5$ or 25. Panel A of the table shows that the steepening indicator can forecast intraday returns on Federal funds and Eurodollar futures at the 1% level for both intraday windows. The steepening indicator can also forecast intraday returns on Treasury futures, although the statistical significance is weaker than that for the short-term interest rate futures. Positive coefficients on STEEP_t mean that today's strong steepening is followed by a positive shock to short-term interest rate futures and Treasury futures at subsequent payroll release times.

Panel A also shows that today's strong steepening is associated with a positive shock to major currency futures at subsequent payroll release times. That is, strong steepening is followed by depreciations of the U.S. dollar against the British pound, Swiss franc, and Japanese yen.[11] The results are statistically significant at the 1% to 10% with the shorter intraday window. However, the steepening indicator has no predictive power for S&P 500 index futures.

Panel B shows that the flattening indicator can forecast intraday returns on short-term interest rate futures and major currency futures, although the statistical significance is weaker than that of the steepening indicator. Negative coefficients on FLAT_t mean that today's strong flattening is followed by a negative shock to short-term interest rate futures and major currency futures at subsequent payroll release times. Like the steepening indicator, the flattening indicator has no predictive power for S&P 500 index futures.

One may wonder why spreading indicators have no predictive power for S&P 500 index futures. The finance literature documents that option volatility spreads (the differences between put- and call-implied volatilities) have predictive power for stock returns, and attributes the finding to informed trading in options markets.[12] Consistent with the literature, I provide some evidence that informed trading may have occurred in the stock index options market just before future payroll releases (see Appendix A.2). In particular, a stronger

[11] I do not use Euro currency futures because of their short sample period.

[12] See, for example, Cremers and Weinbaum (2010), Jin, Livnat, and Zhang (2012), and Chan, Ge, and Lin (2015).

steepening indicator is followed by a greater volatility spread at the market close just before future payroll releases, suggesting that put (call) options tend to become richer (cheaper) just before future payroll releases. In contrast, there is no similar predictive power two days before future payroll releases or the very days of future payroll releases. Overall, the results in the appendix suggest that informed traders may have timed the stock index options market just before payroll announcements.

Private information versus risk premiums: I have showed that spreading indicators have predictive power for asset markets' response to subsequent payroll announcements. There could be two explanations for such predictive power. One explanation is that speculators may have private information about future payrolls that is not impounded into consensus forecasts and futures prices. The other explanation is that macroeconomic announcements are accompanied by a resolution of uncertainty which varies over the business cycle. That said, steepening indicators can predict announcement returns because they are associated with uncertainty or risk premiums.

To tease out the true source of the predictive power, I re-examine the prediction for intraday asset returns after controlling for contemporaneous payroll surprises as follows:

$$\mathrm{r}_{t+h}^{w_-,w_+} = \alpha + \beta \mathrm{SPRD}_t + \eta \mathrm{SURP}_{t+h} + \varepsilon_{t+h}, \tag{10}$$

where SURP_{t+h} denotes the h-month-ahead payroll surprise, the difference between the first-release payroll number and the consensus forecast. If private information is the true source of the predictive power, I expect the coefficient on SPRD_t (β) to become insignificant as SURP_{t+h} is included in the regression. If β is still significant, I interpret the result to imply that the predictive power may come from a non-information source.

Table 6 shows the regression results. The contemporaneous payroll surprise, SURP_{t+h}, can explain a significant fraction of the intraday returns at the 1% level for every asset considered. Importantly, once the payroll surprise is included, both steepening and flattening indicators lose much of the predictive power for the intraday returns. This result is in favor of the information-based explanation that spreading indicators have predictive power for intraday asset returns because they contain private information about future payroll surprises.

Summary and discussion: Spreading indicators predict payroll surprises in following months and asset markets' reaction to subsequent payroll surprises. These results suggest that speculators have private information about future payrolls that is not impounded into consensus forecasts and futures prices. While I find no similar result for other key macroeconomic announcements such as GDPs and industrial productions, payrolls are dubbed the king of announcements by scholars (see Andersen and Bollerslev 1998) and practitioners, and they constitute a key component in the dual mandate of the Federal Reserve. Gilbert, Scotti, Strasser, and Vega (2017) find that payrolls have the biggest effect on U.S. Treasury bond yields.

A surprising aspect of my findings is that information in current spreading indicators is not fully incorporated into the futures prices until the impending payroll announcement. This partial information adjustment may be hard to reconcile with the strategic trading model of Kyle (1985) in which information should be fully incorporated into asset prices as market makers can learn from informed traders' order flows. The result is also puzzling in that the interest rate futures market is highly liquid—one of the largest futures markets.

Why is it that information in spread trading persists so long? A possible explanation can be drawn from the recent literature emphasizing banks' balance sheet costs in the pricing of interest rate derivatives. For example, Du, Tepper, and Verdelhan (2018) find persistent violations of covered interest parity after the 2008 financial crisis and provide evidence that the violations are associated with regulations such as the Basel III leverage-ratio rule. In addition to regulatory constraints, dealer banks account for their own funding costs that are higher than the risk-free rate in trading and hedging derivatives (see Andersen, Duffie, and Song 2019). Most related to my work, Fleckenstein and Longstaff (2020) document persistent bases between Treasury futures and cheapest-to-deliver bonds over the long sample period from 1991 to 2018 and attribute the bases to capital regulations and dealers' funding costs (or debt overhang costs).[13] Given such frictions facing dealer banks, informed speculators may not be able to take their optimal FX exposures, resulting in the departure of futures prices from frictionless equilibrium prices, especially during recessions when the frictions are most binding. Furthermore, Kyle (1989) shows that if futures markets are concentrated in the hands of a finite number of large players, prices are not fully revealing in the limit as noise traders vanish. A reduction in dealers' competition during recessions can be another contributor to long-lived information in spread trading.

2.4 Spread trading versus outright trading

I here compare the information content of spread trading to that of outright trading in various futures markets. This comparison is interesting because investors' macroeconomic expectations can be revealed in other futures markets as well. For example, informed traders may engage in outright trading in short-term bond futures because short-term rates are directed by monetary policy. Piazzesi and Swanson (2008) document that positions in Eurodollar futures have predictive power for excess returns on federal funds futures. Furthermore, business-cycle risk is fundamental to all kinds of asset classes and professional investors rebalance asset allocations along phases of the business cycle. For example, ahead of an impending recession, asset managers may reduce positions in stock and crude oil futures, while increasing positions in safe-haven assets such as Treasury and gold futures.

I consider eight futures markets covering bonds, stocks, currencies, and commodities; and define an outright indicator in each market as the net number of speculators in that market. Let $\widehat{p}_{steep,t}$ and $\widehat{p}_{out,t}$ denote the recession probability forecasts associated with the steepening indicator and the outright indicator in each of the selected futures markets,

[13] The history of the market segmentation repeated itself at the start of the coronavirus pandemic (mid-March 2020).

respectively. A combination forecast, denoted by $\widehat{p}_{fc,t}$, is defined as a convex combination of the two individual forecasts:

$$\widehat{p}_{fc,t} = \lambda \widehat{p}_{steep,t} + (1 - \lambda)\widehat{p}_{out,t}, \tag{11}$$

where λ is the weight given to the forecast associated with the steepening indicator and $(1 - \lambda)$ is the weight given to the forecast associated with the outright indicator. I then implement the forecast encompassing test introduced by Harvey, Leybourne, and Newbold (1998) to see whether λ is equal to 1 or 0. If $\lambda = 1$ (0), then the steepening indicator (the outright indicator) encompasses the information contained in the outright indicator (the steepening indicator).

Panel A of Table 7 shows the results of the forecast encompassing test between the spreading indicator and the outright indicator for various futures markets. As is shown in the table, I reject the null hypothesis $H_{\lambda=0}$, with a p value smaller than 1%, for every outright indicator considered, implying that any of the outright indicators do not encompass the information contained in the steepening indicator. In contrast, I fail to reject the null hypothesis that the steepening indicator encompasses the information contained in the outright indicators in all futures, except for crude oil futures.

I next compare the information content of the steepening indicator to that of the outright indicators in light of payroll growth forecasting. Let $\widehat{g}_{steep,t}$ and $\widehat{g}_{out,t}$ denote the payroll growth forecasts associated with the steepening indicator and the outright indicator, respectively. Panel B of Table 7 shows the results of the forecast encompassing tests between $\widehat{g}_{steep,t}$ and $\widehat{g}_{out,t}$. Again, I reject the null hypothesis $H_{\lambda=0}$, with a p value smaller than 1%, implying that any of the outright indicators do not encompass the information contained in the steepening indicator. In contrast, I fail to reject the null hypothesis that the steepening indicator encompasses the information contained in the outright indicators. Overall, spread trading contains more information about future economic activities than outright trading.

3 Information content for stock returns

This section studies the predictive power of spread trading for the pre-FOMC stock drifts and evaluates the economic gain of a pre-FOMC timing strategy using the information contained in spread trading. An important implication of the results provided in this section is that spread trading contains information about the future course of monetary policy.

3.1 Explaining the pre-FOMC drift puzzle

Predicting pre-FOMC same-day returns: Lucca and Moench (2015) document that a large fraction of stock excess returns have materialized during 24-hour windows prior to scheduled FOMC announcements. To show the association between spread trades and the pre-FOMC stock drift, I obtain a pre-FOMC same-day return, the return on the S&P 500 futures between 9:30 a.m. EST on the day of an FOMC announcement and 15 minutes before the announcement.[14] The high-frequency returns data come from Refinitiv Tick History over the period from September 1997 to June 2020. I then run the following predictive regression for the pre-FOMC same-day return:

$$r_t^{sd} = \beta_0 + \beta_1 \mathrm{STEEP}_{t-d} + \beta_2 \mathrm{VIX}_{t-d} + \beta_3 \mathrm{TMSP}_{t-d} + \beta_4 \mathrm{EBP}_{t-d} + \varepsilon_t, \tag{12}$$

where r_t^{sd} denotes the pre-FOMC same-day return, VIX denotes the Chicago Board of Options Exchange VIX index, and d refers to a lookback period. Here, the time index t denotes an FOMC date. To show the results below, I set the lookback period to be equal to the number of days between the current and last FOMC dates. In this case, the regression essentially tests if the pre-FOMC same-day return is predictable by the explanatory variables observed on the last FOMC announcement day.[15]

Panel A of Table 8 shows the in-sample forecasting power of the steepening indicator

[14] The pre-FOMC same-day return normally captures the return between 9:30 a.m. and 2:00 p.m.
[15] The results are robust to various choices of the lookback period (see Appendix A.3).

for the pre-FOMC same-day returns. With no predictors in the regression, the constant term (β_0) would indicate an average pre-FOMC same-day return. Regression (1) shows that the same-day returns have an average of 18 basis points over my sample period. The average is statistically significant at the 1% level with a t statistic of 3.15, suggesting that stock prices tend to rise in the mornings of FOMC announcements. Regression (2) shows that the steepening indicator has statistically significant power for the same-day returns with a t statistic of 3.94. Unlike the steepening indicator, Regression (3) shows that the VIX and term spreads have little-to-weak predictive power for the same-day returns. While EBP has strong predictive power for the same-day returns, Regression (4) shows that the steepening indicator is still important in predicting the same-day returns at the 1% level after EBP is controlled for. Importantly, as long as the steepening indicator is accounted for in Regressions (2) and (4), the constant term is no longer statistically significant. That is, the same-day stock drift is largely explained by the information contained in the steepening indicator.

Predicting pre-FOMC overnight returns: I next study whether the information in spread trades gets incorporated into stock prices during overnight trading hours prior to FOMC announcements. To do so, I compute a pre-FOMC overnight return, the return between 24 hours before a scheduled FOMC announcement and 9:30 a.m. on the following FOMC day. I then examine the predictive power of the steepening indicator for the pre-FOMC overnight return:

$$r_t^{ov} = \beta_0 + \beta_1 \text{STEEP}_{t-d} + \beta_2 \text{VIX}_{t-d} + \beta_3 \text{TMSP}_{t-d} + \beta_4 \text{EBP}_{t-d} + \varepsilon_t, \tag{13}$$

where r_t^{ov} denotes the pre-FOMC overnight return. The explanatory variables and the look-back period are defined as before.

Panel B of Table 8 shows the regression results for the pre-FOMC overnight returns. Regression (1) shows that the overnight returns have an average of 17 basis points. The average is statistically significant at the 5% level with a t statistic of 2.35, suggesting a pre-

FOMC overnight drift. Regression (2) shows that the steepening indicator has no predictive power for the overnight returns, suggesting little evidence of informed overnight trading. Unlike the steepening indicator, Regression (3) shows that the VIX index and term spreads have predictive power for the overnight returns. A possible explanation for this finding is that the overnight drift may be the result of risk compensation for heightened uncertainty, given that the VIX index and term spreads are associated with uncertainty and the business cycle, respectively.

Predicting pre-FOMC 24-hour returns: Let r_t^{24h} denote the pre-FOMC 24-hour return, the sum of same-day and overnight returns. I then run the predictive regression for the pre-FOMC 24-hour return as follows:

$$r_t^{24h} = \beta_0 + \beta_1 \text{STEEP}_{t-d} + \beta_2 \text{VIX}_{t-d} + \beta_3 \text{TMSP}_{t-d} + \beta_4 \text{EBP}_{t-d} + \varepsilon_t. \tag{14}$$

Panel C of Table 8 shows the regression results for the pre-FOMC 24-hour returns. Regression (1) shows that the pre-FOMC 24-hour returns have an average of 35 basis points in my sample and that the average is statistically significant at the 1% level with a t statistic of 3.20. Regression (2) shows that the steepening indicator has statistically significant power for the pre-FOMC 24-hour return at the 5% level with a t statistic of 2.43. Regression (4) shows that the steepening indicator is still important in predicting the pre-FOMC 24-hour returns at the 5% level even after other control variables are included. As in the case of same-day returns, the constant term is no longer statistically significant when the steepening indicator is included in the regression.

Explanation: Overall, I find that speculators' stronger steepening is followed by larger increases in stock prices during same-day trading hours before subsequent FOMC announcements. Which channel can explain the positive relationship between steepening trades and subsequent pre-FOMC same-day returns? The result cannot be explained by the non-monetary information channel because steepening trades are likely to signal low corporate earnings as they are related to low economic activities. Instead, the result is suggestive of the importance of a policy anticipation channel for explaining the pre-FOMC stock drift. Specifically, financial markets sometimes interpret bad incoming data positively for stocks with the expectation that the Federal Reserve may step in to rescue the economy. In light of my finding, speculators appear to have engaged in informed trading ahead of FOMC announcements in anticipation of an easing policy. That is, the policy anticipation channel appears to be dominant relative to the information channel during pre-FOMC same-day trading hours. This interpretation is consistent with existing literature showing that stock prices tend to increase following easing monetary policies (see Rigobon and Sack 2004; and Bernanke and Kuttner 2005).

3.2 Out-of-sample forecasting and economic gains

I examine the out-of-sample forecasting power of the steepening indicator for the pre-FOMC same-day and overnight returns. To this end, the sample period is divided into two subperiods: the first in-sample estimation period (September 1997 to December 2002) and the out-of-sample evaluation period (January 2003 to June 2020). I then compare the univariate predictive regression model including the steepening indicator to the historical average model.[16] The models are estimated on each FOMC date throughout the out-of-sample evaluation period based on a rolling window. An out-of-sample R^2 measure is defined based on a quadratic loss function.

The left panel of Table 9 shows the out-of-sample forecasting results, including out-of-sample R^2s and Clark and West (2007) test statistics. The panel shows that the steepening indicator has forecasting power for the same-day returns with an R^2 of 16.7%. The result is statistically significant at the 1% level. The explanatory power is greater during recessions than during expansions, consistent with the previous finding that spreading indicators are

[16] Goyal and Welch (2008) show that it is difficult to beat the historical average model in out-of-sample forecasting for stock returns.

particularly informative during recessions.

I next study whether out-of-sample forecasting power can be translated into economic value by introducing an active pre-FOMC timing strategy using the steepening indicator. The active pre-FOMC timing strategy for the same-day returns is defined as follows. On each FOMC date I predict the next pre-FOMC same-day return using the univariate predictive regression model including the steepening indicator. If the predicted same-day return is positive (negative), I buy (sell) stock futures at 9:30 a.m. on the FOMC announcement day and square off the position 15 minutes before the announcement. Note that I use the steepening indicator observed on the last FOMC day, so the data underlying the strategy are observed about 45 days before the FOMC announcement. The procedure is similarly applied for the overnight returns.

The right panel of Table 9 shows that the active pre-FOMC timing strategy yields a Sharpe ratio of 1.059 for the same-day returns. To give some perspective, I compare the active strategy to a naive pre-FOMC strategy that always buys stock futures at 9:30 a.m. on the FOMC announcement day and sells the equal amount 15 minutes before the announcement. The naive pre-FOMC strategy leads to a Sharpe ratio of 0.694 for the same-day returns, which is 0.36 smaller than that of the active strategy. No similar improvement is found for the overnight returns.

Overall, I demonstrate that the steepening indicator has out-of-sample forecasting power for pre-FOMC same-day returns and can deliver some economic gain. Further improvements may be possible in several ways. For example, it would be interesting to combine both information on the steepening indicator and bond excess premiums for the pre-FOMC same-day returns. The preceding results show that the pre-FOMC overnight returns are predictable by the VIX index and term spreads, so it would be interesting to study a pre-FOMC 24-hour timing strategy using the VIX index and term spreads for the overnight component and using the steepening indicator and bond excess premiums for the same-day component. I will leave these possibilities to future research.

3.3 Robustness

Cieslak, Morse, and Vissing-Jorgensen (2019) argue that information has been leaked to the market through policymakers' informal communication with financial media. Therefore, I test if the predictive power of the steepening indicator is robust to the asset market shocks during a lookback period leading up to the FOMC announcement (exclusive of the FOMC date) as follows:

$$r_t^{sd} = \beta_0 + \beta_1 \text{STEEP}_{t-d} + \beta_2 \Delta\text{OIS}_{t-1|t-d} + \beta_3 \Delta\text{LIBOR}_{t-1|t-d} + \beta_4 \Delta\text{SPX}_{t-1|t-d} + \varepsilon_t, \tag{15}$$

where $\Delta\text{OIS}_{t-1|t-d}$ is a three-month overnight index swap (OIS) rate change between date $t-d$ and $t-1$, $\Delta\text{LIBOR}_{t-1|t-d}$ is a three-month LIBOR change between $t-d$ and $t-1$, and $\Delta\text{SPX}_{t-1|t-d}$ is a S&P index log return between $t-d$ and $t-1$. If there is gradual information leakage before FOMC announcements, the predictive power of the steepening indicator may be reduced by the asset market shocks—the control variables that I include to capture the information that might have arrived until the day before an FOMC announcement.

Table 10 shows the robustness results for the pre-FOMC same-day returns with a lookback period of one week to two months. The table shows that the predictive power of the steepening indicator remains intact even after the asset market shocks are included. This result holds regardless of various choices of a lookback period up to two months. Interestingly, the S&P 500 index shock is statistically significant at the 5% level with a lookback period of two weeks or one month. The negative coefficient on the S&P 500 index shock may be explained by expectations that the Federal Reserve is more likely to take an easing policy following stock market drops, practitioners' belief called a Fed put.

According to my analysis, information in steepening trades is impounded into stock prices mostly during pre-FOMC same-day trading hours. This last-hour trading behavior may be explained by the literature suggesting a stealth motive in informed trading. For example, Foster and Viswanathan (1994) provide a dynamic model of strategic trading with two informed traders in which one has more information than the other while both share some common information. The model shows that exclusively private information gets incorporated into asset prices in the last trading periods as the more informed tries to avoid revealing information to the less informed. That said, the last-hour informed trading that I have found is consistent with my argument that speculators have some private information.

Aside from the stealth motive, there are two additional reasons why informed trading is particularly active during pre-FOMC same-day trading hours. First, as long as intraday trading is completely squared off until the day's market close, it does not incur any extra margin (although a very small intraday margin can be temporarily required). As a result, same-day trading is more practically feasible than overnight trading even if informed traders face a binding capital constraint during recessions. Second, an overnight position can be too risky because it is difficult to pay attention to overnight news and to square off the position immediately because of lack of market liquidity.

4 Information content for the yield curve

The results in Sections 2 and 3 suggest that speculators' spreading indicators contain unique information about future economic activity and monetary policy. If this is indeed the case, the steepening indicator should be able to forecast changes in Treasury yields. Accordingly, this section examines the information content of spread trading for variations in the Treasury yield curve.

4.1 Forecasting yield changes

To examine the forecasting power of the steepening indicator for yield changes, I obtain a monthly yield change as $\Delta y_t^T = y_t^T - y_{t-1}^T$, where y_t^T denotes the Treasury par yield with a maturity of T at the end of month t. Here, I divide the entire sample period into two subperiods: the first in-sample estimation period (July 1986–December 1999) and the out-of-sample evaluation period (January 2000–June 2020). The models are recursively estimated at each point in time throughout the out-of-sample evaluation period. The out-of-sample R^2 is measured using a quadratic loss function.

Panel A of Table 11 presents the out-of-sample forecasting power of STEEP for h-month-ahead yield changes when the historical average is selected as a benchmark model. The panel shows that STEEP has statistically significant forecasting power at the 1% level for short-term yield changes with three-month to one-year maturities and at the 5% level for yield changes with two-year maturities. The average coefficients on the steepening indicator are negative for short-term yield changes, implying that today's strong steepening is followed by a decrease in short-term Treasury yields in subsequent months. However, the steepening indicator does not have statistically significant power for long-term yield changes.

To understand why the result is insignificant for long-term yield changes, I separate them into two components, changes in expected interest rates and changes in term premiums, using the decomposed data provided by Kim and Wright (2005). I then test the predictive power of the steepening indicator for each of the two components. Although not reported in this paper, I find modest evidence that the steepening indicator predicts expected interest rates and risk premiums in opposite directions, making the prediction of long-term yield changes ambiguous.

Panel B of Table 11 presents the out-of-sample forecasting power after TMSP is controlled for. As before, STEEP has statistically significant forecasting power at the 1% level for short-term yield changes with three-month to one-year maturities and at the 1% or 5% level for yield changes with two-year maturities. This result suggests that the steepening indicator has very different information about future interest rates than term spreads, a finding consistent with low correlations between STEEP and TMSP (see Table 1).

Panel C of Table 11 presents the out-of-sample forecasting power after EBP is controlled for. The steepening indicator yields a lower value of R^2 and a weaker statistical significance in Panel C (with EBP as a control) than in Panel A (with no control). This result suggests that the predictive information in the steepening indicator is partly explained by bond excess premiums. Nevertheless, STEEP has statistically significant power at the 1% to 5% level for short-term yield changes with three-month to one-year maturities.

4.2 Forecasting slope changes

I now test whether the steepening indicator can help predict changes in the slope of the yield curve. To do so, I define a slope change as the monthly change in a yield spread between T-year Treasury bond and three-month Treasury bill. That is, $\Delta s_t^T = \Delta y_t^T - \Delta y_t^{3M}$, where Δs_t^T denotes the slope change with a maturity of T between month t and $t-1$.

Table 12 shows the out-of-sample forecasting performance of the steepening indicator for the h-month-ahead slope changes, Δs_{t+h}^T. Panel A presents the forecasting power of STEEP relative to the historical-average model. Note that the average coefficients ($\overline{\beta}$) are positive, meaning that strong steepening is followed by an increase in the slope of the Treasury yield curve (that is, an increase in long-term yields relative to short-term yields). The results are statistically significant at the 1% level in one-month-ahead forecasting and at the 1% or 5% level in three-month-ahead forecasting. In addition, the out-of-sample forecasting performance is greater during recessions than during expansions ($R^2_{Rec} > R^2_{Exp}$).

Panel B of Table 12 presents the out-of-sample forecasting power after TMSP is controlled for. STEEP has incremental forecasting power beyond term spreads, with an out-of-sample R^2 between 4.6% and 6.8% (one month ahead) or between 1.0% and 2.6% (three months ahead). In particular, the forecasting power (R^2) becomes greater as the maturity of Treasury bonds increases. The statistical significance is obtained at the 1% level in one-month-ahead forecasting and at the 1% or 5% level in three-month-ahead forecasting.

Panel C of Table 12 presents the out-of-sample forecasting power after EBP is controlled for. In one-month-ahead forecasting, STEEP has statistically significant forecasting power at the 1% level for every maturity considered, with an out-of-sample R^2 between 3.9% and 4.8%. However, in three-month-ahead forecasting, STEEP substantially loses predictive power to some extent after EBP is controlled for.

4.3 Summary and related literature

Spread trading contains useful information for predicting variations in the Treasury yield curve. Specifically, strong steepening is followed by a reduction in short-term yields and an increase in the slope of the yield curve in subsequent months. Evidence is consistent with the earlier finding that strong steepening is associated with lower economic activities and higher expectations of monetary easing in following months.

My results add to the literature on the determinants of bond prices and risk premiums. A widely-held belief in this area is that macroeconomic information should be a key determinant of the term structure of interest rates. While a number of researchers, including Diebold, Rudebusch, and Aruoba (2006), Ludvigson and Ng (2009), and Joslin, Priebsch, and Singleton (2014), provide evidence consistent with such a belief, Bauer and Hamilton (2017) argue that the importance of macroeconomic information may be weaker than what is shown in the original papers because the underlying statistical tests are subject to finite-sample distortions. In addition, Duffee (2011) finds that, while changes in short-term rates and bond risk premiums are associated with a hidden factor from the cross-section of yields, macroeconomic variables can explain only a small fraction of the variation in the hidden factor. Overall, while macroeconomic factors in bond prices and risk premiums are still under investigation, my results suggest that sophisticated investors' superior information helps explain the time-evolution of the yield curve.

5 Policy implications

I draw two policy implications from my findings. First, with growing evidence on information leakage before macroeconomic and FOMC announcements, policymakers have been more and more concerned about safeguarding confidential information. For example, Bernile, Hu, and Tang (2016) find that abnormal pre-FOMC order imbalances are aligned with subsequent policy surprises and attribute the alignment to information leakage. Cieslak, Morse, and Vissing-Jorgensen (2019) argue that policymakers' informal communication with the financial media and markets generates a cyclical pattern of stock returns over the FOMC cycle. Kurov, Sancetta, Strasser, and Wolfe (2019) discover similar evidence of informed trading right before several macroeconomic announcements. However, I show that the pre-FOMC same-day drift is predictable by the steepening indicator observed on the last FOMC announcement day. Unless information leakage is similarly predictable by the lagged steepening indicator, the pre-announcement drift may be driven by the strategic informed trading by speculators with a superior ability to form macroeconomic expectations. Note that I do not dismiss the possibility of information leakage, but rather argue that pre-announcement drifts are driven by not only information leakage but also strategic informed trading. Therefore, the existence of a pre-announcement drift itself should not be considered to be sufficient evidence for information leakage.

Second, spreading indicators as introduced in this paper can be useful for policymakers (and investors with informational disadvantage) as they reflect the market's expectations on future economic activity and monetary policy. To illustrate practical usefulness, I zero in on the evolution of spreading indicators leading up to and surrounding the coronavirus pandemic. As shown in Figure 4, the steepening indicator reached the maximum point immediately after the first policy rate cut in the ongoing easing cycle that began on August 1, 2019. Interestingly, the steepening indicator climbed to the top again before end-February

2020, suggesting that speculators moved one step ahead of the Great Lockdown (March 15).[17] As of end-June 2020, while the steepening indicator came back down, the flattening indicator started to rise. Considering that the OIS-implied policy rates remain near the zero lower bound a few years ahead, the rise in the flattening indicator is unlikely to signal that the Federal Reserve will start rolling back the current easing cycle anytime soon. Instead, a more likely explanation is that the increasing flattening position is driven by safe-haven or reach-for-yield demands for long-term Treasury bonds—a bull flattener. More broadly, my findings suggest that informed traders' strategies and positions, if properly identified, can help policymakers and practitioners understand the future state of the economy.

6 Conclusion

The slope of the yield curve is closely linked to the real economy and monetary policy. Using positions data on bond futures, I study the information content of speculators' spread trading for future economic activity and asset prices. I first find that strong steepening trades are associated with higher subsequent recession probabilities and lower subsequent payroll growths. The predictive power cannot be spanned by other business-cycle indicators such as term spreads and bond excess premiums. I attribute part of the predictive power to speculators' superior ability to form expectations on future payrolls because their spread positions are aligned with subsequent payroll surprises and asset markets' reaction to the payroll surprises.

I also find that the information in spread trades plays a key role in explaining the pre-FOMC stock drift puzzle. Specifically, speculators' strong steepening is followed by larger increases in stock prices during a few trading hours before subsequent FOMC announcements. I interpret the result to imply that informed speculators engage in pre-FOMC same-day

[17] According to the financial media, some hedge funds recorded big gains during the coronavirus market selloffs.

trading in anticipation of an easing policy. Steepening trades also help predict variations in the Treasury yield curve in following months. Specifically, stronger steepening is followed by a reduction in short-term yields and an increase in the slope of the yield curve. Overall, speculators' spread trading contains predictive information about economic activities and asset prices, and thus, can be useful as a leading economic indicator for policymakers and practitioners.

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Table 1: **Summary statistics and correlation matrix**

This table shows the summary statistics of the business-cycle indicators and the correlation matrix among them. STEEP denotes the steepening indicator implied by speculators' positions in bond futures; FLAT denotes the flattening indicator implied by speculators' positions in bond futures; TMSP denotes term spreads, the quarterly moving averages of the yield spreads between ten-year Treasury bonds and three-month Treasury bills; EBP denotes the bond excess premiums as calculated by Gilchrist and Zakrajšek (2012); and FFR denotes real federal fund rates, the differences between the effective federal fund rates and the inflation rates as implied by the core PCE price index. The sample spans from July 1986 to June 2020.

	STEEP	FLAT	TMSP	EBP	FFR
Panel A: Summary statistics					
Mean	0.38	0.35	1.78	0.06	1.22
Median	0.31	0.17	1.77	-0.10	0.42
Min.	0.00	0.00	-0.49	-1.11	-2.01
Max.	1.00	1.00	3.74	3.47	5.50
Std.	0.38	0.38	1.09	0.62	2.18
Skew.	0.44	0.64	-0.09	2.16	0.22
Kurt.	1.64	1.80	1.95	9.94	1.54
AR(1)	0.92	0.95	0.98	0.91	0.99
Panel B: Correlation matrix					
STEEP	1.00	-0.75	-0.04	0.36	0.07
FLAT		1.00	-0.09	-0.25	-0.11
TMSP			1.00	0.03	-0.51
EBP				1.00	0.04
FFR					1.00

Table 2: **Information content for economic activity: In-sample evidence**

This table shows the in-sample forecasting power of spreading indicators for economic activity. Panel A reports the h-month-ahead Probit regression results for recession probabilities with the sample period from July 1986 to June 2020. Panel B reports the h-month-ahead linear regression results for the first-release non-farm payroll growth rates with the sample period from July 1986 to March 2020. STEEP denotes the steepening indicator implied by speculators' positions in bond futures; FLAT denotes the flattening indicator implied by speculators' positions in bond futures; TMSP denotes term spreads, the quarterly moving averages of the yield spreads between ten-year Treasury bonds and three-month Treasury bills; EBP denotes the bond excess premiums as calculated by Gilchrist and Zakrajšek (2012); and FFR denotes real federal fund rates, the differences between the effective federal fund rates and the inflation rates as implied by the core PCE price index. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	STEEP as a predictor				FLAT as a predictor		
	3 months ahead	6 months	12 months		3 months ahead	6 months	12 months
Panel A: Forecasting recession probabilities							
STEEP	2.02***	1.91***	1.05***	FLAT	-1.63***	-1.55***	-0.95**
	(4.32)	(4.28)	(3.10)		(-2.76)	(-2.84)	(-2.29)
TMSP	-0.38**	-0.84***	-1.09***	TMSP	-0.43***	-0.87***	-1.14***
	(-2.19)	(-3.94)	(-4.91)		(-2.71)	(-4.31)	(-5.15)
EBP	0.56***	0.56***	0.26**	EBP	0.61***	0.59***	0.29***
	(5.24)	(4.88)	(2.33)		(6.16)	(5.51)	(2.65)
FFR	0.22	0.19	0.16	FFR	0.06	0.02	0.06
	(1.12)	(0.98)	(0.85)		(0.38)	(0.11)	(0.34)
Const.	-2.60***	-1.97***	-1.01**	Const.	-0.85**	-0.31	-0.07
	(-4.49)	(-3.65)	(-2.30)		(-2.53)	(-0.91)	(-0.20)
pseudo R^2	44.8	46.7	42.9	*pseudo* R^2	38.1	40.7	41.0
NOBS	405	402	396	NOBS	405	402	396
Panel B: Forecasting non-farm payroll growth rates							
STEEP	-1.14***	-1.37***	-1.07***	FLAT	0.77***	0.91***	0.92***
	(-5.18)	(-4.93)	(-3.20)		(3.74)	(3.71)	(2.88)
TMSP	0.19*	0.35***	0.54***	TMSP	0.25**	0.42***	0.62***
	(1.91)	(3.15)	(3.43)		(2.55)	(3.65)	(3.53)
EBP	-0.49***	-0.53***	-0.37**	EBP	-0.56***	-0.62***	-0.42***
	(-3.78)	(-4.42)	(-2.39)		(-4.06)	(-4.64)	(-2.79)
FFR	0.33***	0.36***	0.20	FFR	0.35***	0.39**	0.25*
	(2.66)	(2.64)	(1.49)		(2.60)	(2.55)	(1.65)
Lagged	0.53***	0.30***	0.19	Lagged	0.58***	0.36***	0.21
	(4.60)	(2.60)	(1.31)		(4.75)	(3.19)	(1.43)
Const.	0.76***	0.69***	0.38	Const.	-0.09	-0.31	-0.53
	(3.43)	(2.91)	(1.04)		(-0.35)	(-0.99)	(-1.05)
adj. R^2	41.7	36.6	22.4	*adj.* R^2	39.4	33.1	21.5
NOBS	402	399	393	NOBS	402	399	393

Table 3: **Information content for economic activity: Out-of-sample evidence**

This table shows the out-of-sample forecasting power of spreading indicators for economic activity. Panels A and B correspond to the prediction of recession probabilities (with the sample period from July 1986 to June 2020) and the prediction of first-release non-farm payroll growth rates (with the sample period from July 1986 to March 2020), respectively. STEEP denotes the steepening indicator implied by speculators' positions in bond futures, and FLAT denotes the flattening indicator implied by speculators' positions in bond futures. In each panel, I divide the entire sample period into two subperiods: the first in-sample estimation period (July 1986 to December 1999) and the out-of-sample evaluation period (January 2000 to the sample-end). The models are recursively estimated at each point in time throughout the out-of-sample evaluation period. I then measure the incremental forecasting power of spreading indicators beyond term spreads and bond excess premiums by comparing the models with and without the spreading indicator. The out-of-sample R^2 is measured using the log loss function for forecasting recession probabilities and using the quadratic loss function for forecasting the first-release non-farm payroll growth rates. The McCracken (2007) test is applied to compare two nested models. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. $\overline{\beta}$ denotes an average of the coefficients on the spread indicator over the out-of-sample evaluation period. The out-of-sample R^2 is further broken down into two subperiods, recessions and expansions, which are denoted by R^2_{Rec} and R^2_{Exp}, respectively.

	3 months ahead					6 months ahead				
	$\overline{\beta}$	R^2	Statistic	R^2_{Rec}	R^2_{Exp}	$\overline{\beta}$	R^2	Statistic	R^2_{Rec}	R^2_{Exp}
Panel A: Forecasting recession probabilities										
After controlling for term spreads										
STEEP	2.14	30.0	1.98***	41.2	-6.1	1.87	24.8	1.56***	37.0	-10.8
FLAT	-1.80	17.2	2.28***	19.4	10.2	-1.16	14.1	1.89***	13.5	15.9
After controlling for bond excess premiums										
STEEP	1.57	15.9	1.23**	33.5	-19.8	1.19	8.3	0.99**	23.7	-13.7
FLAT	-1.05	7.3	1.82***	9.5	2.9	-0.60	3.5	1.64***	1.3	6.6
Panel B: Forecasting non-farm payroll growth rates										
After controlling for term spreads										
STEEP	-1.35	14.4	2.18***	25.4	6.7	-1.50	16.8	2.16***	22.2	11.8
FLAT	0.90	4.5	1.74***	6.8	2.8	1.02	5.4	1.83***	7.9	3.1
After controlling for bond excess premiums										
STEEP	-1.10	8.9	2.04***	16.1	5.7	-1.22	12.6	2.47***	16.8	9.8
FLAT	0.66	1.2	0.50*	-1.0	2.2	0.67	3.0	1.37***	1.5	3.9

Table 4: **Forecasting future payrolls beyond consensus forecasts**

This table shows the following regression results for future payrolls:

$$\text{NFP}_{t+h} = \alpha + \beta\widetilde{\text{NFP}_{t+h}} + \gamma\text{SPRD}_t + \eta' z_t + \varepsilon_{t+h},$$

where NFP_{t+h} and $\widetilde{\text{NFP}_{t+h}}$ denote the first-release payroll number and the consensus forecast for month $t+h$, respectively, and SPRD_t denotes either STEEP_t or FLAT_t. Note that the information between month t and $t+h$ is visible to professional forecasters but not to speculators in bond futures. STEEP denotes the steepening indicator implied by speculators' positions in bond futures; FLAT denotes the flattening indicator implied by speculators' positions in bond futures; TMSP denotes term spreads, the quarterly moving averages of the yield spreads between ten-year Treasury bonds and three-month Treasury bills; EBP denotes the bond excess premiums as calculated by Gilchrist and Zakrajšek (2012); and FFR denotes real federal fund rates, the differences between the effective federal fund rates and the inflation rates as implied by the core PCE price index. The sample spans from January 1988 to March 2020. Panels A and B show the predictive power of the steepening and flattening indicators, respectively, for various forecast horizons. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
Panel A: Using the steepening indicator ($\text{SPRD}_t = \text{STEEP}_t$)						
$\widetilde{\text{NFP}_{t+h}}$	1.01***	1.02***	1.01***	0.97***	0.99***	1.02***
	(16.61)	(15.46)	(15.28)	(14.43)	(15.98)	(17.64)
STEEP	-23.33*	-28.01**	-39.69***	-42.78***	-39.89***	-17.22
	(-1.87)	(-2.10)	(-2.81)	(-3.11)	(-2.82)	(-1.18)
TMSP	1.60	2.47	0.36	1.58	5.24	5.75
	(0.27)	(0.40)	(0.06)	(0.26)	(0.80)	(0.88)
EBP	-3.06	0.95	2.86	-3.06	-0.20	-0.05
	(-0.44)	(0.13)	(0.39)	(-0.41)	(-0.02)	(-0.01)
FFR	-0.41	-0.29	-1.81	-0.71	1.23	-0.56
	(-0.07)	(-0.05)	(-0.32)	(-0.12)	(0.19)	(-0.09)
Const.	-6.10	-7.36	1.72	4.85	-5.25	-17.68
	(-0.36)	(-0.40)	(0.10)	(0.26)	(-0.30)	(-1.03)
adj. R^2	70.4	70.5	71.3	71.3	71.3	70.9
NOBS	387	386	385	384	383	382
Panel B: Using the flattening indicator ($\text{SPRD}_t = \text{FLAT}_t$)						
$\widetilde{\text{NFP}_{t+h}}$	1.02***	1.04***	1.03***	1.00***	1.01***	1.01***
	(16.07)	(15.60)	(15.68)	(15.57)	(16.84)	(18.24)
FLAT	12.28	11.16	19.30	28.01**	33.26**	32.27**
	(0.90)	(0.81)	(1.41)	(2.15)	(2.41)	(2.46)
TMSP	2.61	3.32	1.81	3.75	7.91	8.97
	(0.43)	(0.53)	(0.31)	(0.60)	(1.14)	(1.27)
EBP	-4.24	-0.33	1.39	-4.11	-0.81	-0.28
	(-0.59)	(-0.04)	(0.18)	(-0.53)	(-0.10)	(-0.04)
FFR	-0.45	-0.76	-2.09	-0.20	2.53	2.21
	(-0.07)	(-0.12)	(-0.34)	(-0.03)	(0.36)	(0.33)
Const.	-22.30	-25.23	-25.41	-28.19	-39.79**	-41.50**
	(-1.30)	(-1.49)	(-1.54)	(-1.63)	(-2.08)	(-2.23)
adj. R^2	70.3	70.3	70.9	71.0	71.2	71.2
NOBS	387	386	385	384	383	382

Table 5: **Predicting asset markets' response to payroll releases**

This table tests if spreading indicators can predict intraday returns on various futures at subsequent payroll release times as follows:

$$\mathrm{r}_{t+h}^{w_-,w_+} = \alpha + \beta \mathrm{SPRD}_t + \eta' z_t + \varepsilon_{t+h},$$

where $\mathrm{r}_{t+h}^{w_-,w_+}$ denotes the intraday return on a futures contract over the short window starting w_- minutes before the h-month-ahead payroll release time and ending w_+ minutes after. SPRD_t denotes either the steepening indicator or the flattening indicator. The sample spans from June 1996 to June 2020. Panels A and B show the predictive ability of the steepening and flattening indicators with $h = 3$ months, respectively. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$(w_-, w_+) = (5, 5)$					$(w_-, w_+) = (5, 25)$				
Futures	SPRD	TMSP	EBP	Const.	*adj.* R^2	SPRD	TMSP	EBP	Const.	*adj.* R^2
Panel A: Using the steepening indicator ($\mathbf{SPRD}_t = \mathbf{STEEP}_t$)										
Federal funds	1.24***	-0.10	0.02	-0.20	2.5	1.41***	-0.04	-0.09	-0.34	2.4
	(2.80)	(-0.66)	(0.08)	(-0.63)		(3.16)	(-0.26)	(-0.39)	(-1.22)	
Eurodollar	1.82***	0.05	-0.25	-0.65	1.9	1.99***	0.08	-0.28	-0.76*	2.4
	(3.24)	(0.25)	(-0.85)	(-1.59)		(3.69)	(0.40)	(-0.97)	(-1.84)	
2-yr Treas.	3.73**	0.75	-1.51*	-2.56**	0.8	3.96**	0.85	-1.84*	-2.81**	1.2
	(2.55)	(1.42)	(-1.68)	(-2.19)		(2.46)	(1.54)	(-1.87)	(-2.31)	
5-yr Treas.	9.43**	2.43*	-5.35**	-7.14**	1.5	7.55**	2.92**	-4.85**	-6.94**	1.3
	(2.46)	(1.94)	(-2.30)	(-2.59)		(1.99)	(2.26)	(-2.30)	(-2.57)	
10-yr Treas.	12.69**	3.04*	-6.93**	-9.39**	1.3	9.22*	4.15**	-5.95**	-9.42**	1.0
	(2.39)	(1.71)	(-2.28)	(-2.43)		(1.76)	(2.29)	(-2.14)	(-2.48)	
30-yr Treas.	16.66**	3.17	-8.04*	-12.41**	0.7	10.75	5.01*	-5.57	-12.10**	0.3
	(2.20)	(1.26)	(-1.96)	(-2.35)		(1.45)	(1.85)	(-1.37)	(-2.14)	
S&P 500	-10.04	-2.77	2.05	13.50***	-0.0	-6.86	-3.76	-2.21	12.67**	0.2
	(-1.36)	(-1.11)	(0.41)	(2.98)		(-0.85)	(-1.35)	(-0.42)	(2.36)	
British pound	6.76*	1.97*	-1.07	-4.38*	1.2	8.86**	1.67	-8.00***	-5.76**	2.5
	(1.93)	(1.72)	(-0.40)	(-1.96)		(2.06)	(1.10)	(-3.63)	(-2.22)	
Swiss franc	11.88**	2.76	-2.69	-7.83**	1.4	11.38*	1.82	-7.57**	-7.55*	0.7
	(2.32)	(1.56)	(-0.90)	(-2.36)		(1.85)	(0.81)	(-2.37)	(-1.83)	
Japanese yen	12.59***	0.61	-7.81***	-4.62	1.7	8.57	1.42	-8.44**	-4.99	0.7
	(2.73)	(0.36)	(-2.70)	(-1.51)		(1.53)	(0.68)	(-2.36)	(-1.23)	
Panel B: Using the flattening indicator ($\mathbf{SPRD}_t = \mathbf{FLAT}_t$)										
Federal funds	-0.83**	-0.14	0.20	0.67	1.1	-0.87**	-0.08	0.12	0.61	0.7
	(-2.44)	(-0.88)	(0.90)	(1.56)		(-2.37)	(-0.52)	(0.53)	(1.32)	
Eurodollar	-1.18**	-0.01	0.02	0.60	0.5	-1.33***	0.02	0.01	0.63	0.8
	(-2.53)	(-0.03)	(0.07)	(1.02)		(-3.03)	(0.08)	(0.04)	(1.09)	
2-yr Treas.	-2.06	0.65	-0.90	-0.17	-0.0	-2.09	0.76	-1.18	-0.32	0.2
	(-1.54)	(1.16)	(-1.07)	(-0.11)		(-1.56)	(1.26)	(-1.28)	(-0.19)	
5-yr Treas.	-5.31	2.18*	-3.83*	-1.05	0.7	-5.02	2.67**	-3.73*	-1.69	0.9
	(-1.61)	(1.67)	(-1.76)	(-0.30)		(-1.54)	(1.98)	(-1.89)	(-0.47)	
10-yr Treas.	-6.57	2.73	-4.80*	-1.46	0.4	-5.32	3.89**	-4.48*	-3.40	0.6
	(-1.44)	(1.50)	(-1.70)	(-0.30)		(-1.17)	(2.08)	(-1.71)	(-0.70)	
30-yr Treas.	-6.92	2.88	-5.03	-2.81	-0.2	-4.37	4.82*	-3.62	-5.95	-0.1
	(-1.13)	(1.12)	(-1.33)	(-0.41)		(-0.66)	(1.74)	(-0.95)	(-0.84)	
S&P 500	-2.07	-3.00	-0.56	10.68	-0.6	-4.25	-4.12	-4.35	12.10	0.0
	(-0.36)	(-1.11)	(-0.11)	(1.48)		(-0.60)	(-1.35)	(-0.88)	(1.55)	
British pound	-6.23*	1.63	-0.30	1.14	1.2	-8.76**	1.19	-7.07***	1.75	2.7
	(-1.88)	(1.39)	(-0.12)	(0.38)		(-2.53)	(0.80)	(-3.54)	(0.47)	
Swiss franc	-9.42**	2.27	-1.13	1.14	0.9	-9.06*	1.35	-6.09**	1.05	0.4
	(-2.00)	(1.24)	(-0.42)	(0.27)		(-1.75)	(0.59)	(-2.04)	(0.20)	
Japanese yen	-7.67*	0.23	-5.85**	3.79	0.7	-4.01	1.24	-6.95**	0.16	0.3
	(-1.74)	(0.13)	(-2.18)	(0.84)		(-0.66)	(0.58)	(-2.01)	(0.03)	

Table 6: **Predicting asset markets' response to payroll releases after controlling for payroll surprises**

This table tests if spreading indicators can predict intraday returns on various futures at subsequent payroll release times after payroll surprises are controlled for:

$$\mathrm{r}_{t+h}^{w_-,w_+} = \alpha + \beta \mathrm{SPRD}_t + \eta \mathrm{SURP}_{t+h} + \varepsilon_{t+h},$$

where $\mathrm{r}_{t+h}^{w_-,w_+}$ denotes the intraday return on a futures contract over the short window starting w_- minutes before the h-month-ahead payroll release time and ending w_+ minutes after. SURP_{t+h} denotes the h-month-ahead payroll surprise, the difference between the first-release payroll number and the consensus forecast. SPRD_t denotes either the steepening indicator or the flattening indicator. Panels A and B show the predictive ability of the steepening and flattening indicators with $h = 3$ months, respectively. The sample spans from June 1996 to March 2020. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$(w_-, w_+) = (5, 5)$				$(w_-, w_+) = (5, 25)$			
Futures	SPRD_t	SURP_{t+h}	Const.	*adj.* R^2	SPRD_t	SURP_{t+h}	Const.	*adj.* R^2
Panel A: Using the steepening indicator ($\mathrm{SPRD}_t = \mathrm{STEEP}_t$)								
Federal funds	0.71**	-0.02***	-0.30**	23.9	0.75**	-0.02***	-0.30**	24.8
	(2.09)	(-6.50)	(-2.21)		(2.17)	(-5.96)	(-2.19)	
Eurodollar	0.64	-0.03***	-0.38**	37.9	0.84*	-0.03***	-0.43**	33.5
	(1.43)	(-7.35)	(-1.98)		(1.88)	(-6.75)	(-1.99)	
2-yr Treas.	-0.36	-0.09***	-0.60	37.1	-0.33	-0.09***	-0.59	36.2
	(-0.32)	(-6.59)	(-1.07)		(-0.27)	(-6.72)	(-0.93)	
5-yr Treas.	-1.84	-0.22***	-0.91	38.6	-3.25	-0.22***	-0.05	36.8
	(-0.58)	(-6.61)	(-0.61)		(-1.06)	(-6.86)	(-0.03)	
10-yr Treas.	-2.69	-0.31***	-1.41	39.7	-5.00	-0.30***	0.06	35.5
	(-0.63)	(-6.96)	(-0.71)		(-1.14)	(-6.72)	(0.03)	
30-yr Treas.	-3.09	-0.41***	-3.50	37.0	-7.02	-0.42***	-0.86	32.6
	(-0.51)	(-6.37)	(-1.20)		(-1.13)	(-6.29)	(-0.25)	
S&P 500	-1.47	0.23***	8.20***	15.2	-1.27	0.24***	6.71**	13.2
	(-0.26)	(4.08)	(3.35)		(-0.20)	(4.36)	(2.00)	
British pound	2.14	-0.12***	-0.42	20.3	-2.27	-0.16***	-0.34	20.9
	(0.64)	(-4.61)	(-0.26)		(-0.62)	(-5.23)	(-0.19)	
Swiss franc	3.60	-0.19***	-1.87	22.7	-2.94	-0.26***	-1.58	25.0
	(0.81)	(-4.82)	(-0.84)		(-0.62)	(-5.99)	(-0.58)	
Japanese yen	0.28	-0.19***	-0.81	21.4	-5.35	-0.23***	0.43	20.0
	(0.07)	(-5.40)	(-0.40)		(-1.07)	(-5.52)	(0.15)	
Panel B: Using the flattening indicator ($\mathrm{SPRD}_t = \mathrm{FLAT}_t$)								
Federal funds	-0.54**	-0.02***	0.18	23.5	-0.55*	-0.02***	0.20	24.4
	(-1.97)	(-6.50)	(1.06)		(-1.93)	(-5.99)	(0.95)	
Eurodollar	-0.63*	-0.03***	0.10	37.9	-0.81**	-0.03***	0.20	33.5
	(-1.77)	(-7.36)	(0.39)		(-2.21)	(-6.78)	(0.74)	
2-yr Treas.	-0.30	-0.09***	-0.63	37.1	-0.28	-0.09***	-0.62	36.2
	(-0.30)	(-6.55)	(-0.85)		(-0.27)	(-6.66)	(-0.81)	
5-yr Treas.	-0.55	-0.22***	-1.44	38.5	-0.57	-0.22***	-1.13	36.6
	(-0.21)	(-6.58)	(-0.78)		(-0.22)	(-6.76)	(-0.62)	
10-yr Treas.	-0.00	-0.31***	-2.48	39.7	0.37	-0.30***	-2.05	35.2
	(-0.00)	(-6.91)	(-1.00)		(0.10)	(-6.63)	(-0.79)	
30-yr Treas.	1.63	-0.41***	-5.31	37.0	2.68	-0.41***	-4.61	32.4
	(0.33)	(-6.32)	(-1.48)		(0.49)	(-6.21)	(-1.20)	
S&P 500	-4.37	0.23***	9.19***	15.4	-4.58	0.24***	7.85**	13.4
	(-0.92)	(4.09)	(2.76)		(-0.75)	(4.39)	(2.14)	
British pound	-4.62	-0.12***	2.11	20.9	-3.43	-0.16***	0.01	21.0
	(-1.65)	(-4.72)	(1.27)		(-1.18)	(-5.17)	(0.01)	
Swiss franc	-6.33	-0.19***	1.86	23.1	-2.28	-0.26***	-1.90	25.0
	(-1.64)	(-4.89)	(0.79)		(-0.55)	(-5.98)	(-0.74)	
Japanese yen	-1.70	-0.19***	-0.08	21.4	2.58	-0.23***	-2.62	19.8
	(-0.49)	(-5.42)	(-0.04)		(0.54)	(-5.56)	(-0.90)	

Table 7: **Forecast encompassing test results between steepening trades and outright trades**

This table shows the results of the Harvey, Leybourne, and Newbold (1998) forecast encompassing test between the steepening indicator and outright indicators in various futures markets. λ is the weight given to the forecast associated with the steepening indicator. The null hypothesis denoted by $H_{\lambda=0}$ tests whether the information contained in the outright indicator encompasses that in the steepening indicator. The null hypothesis denoted by $H_{\lambda=1}$ tests whether the information contained in the steepening indicator encompasses that in the outright indicator. Panels A and B correspond to the prediction of recession probabilities (with the sample period from July 1986 to June 2020) and the prediction of first-release non-farm payroll growth rates (with the sample period from July 1986 to March 2020), respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	3 months ahead			6 months ahead		
		p value			p value	
Futures	λ	$H_{\lambda=0}$	$H_{\lambda=1}$	λ	$H_{\lambda=0}$	$H_{\lambda=1}$
Panel A: Forecasting recession probabilities						
Eurodollar	0.81	0.003***	0.211	1.33	0.000***	0.855
10-yr Treas.	0.87	0.000***	0.250	0.70	0.001***	0.087*
30-yr Treas.	1.08	0.000***	0.653	1.00	0.000***	0.507
S&P 500	1.20	0.000***	0.807	1.32	0.000***	0.894
British pound	1.07	0.000***	0.691	1.20	0.000***	0.821
Japanese yen	0.97	0.000***	0.445	1.02	0.000***	0.542
Gold	1.01	0.000***	0.519	1.09	0.000***	0.716
WTI	0.59	0.000***	0.003***	0.62	0.000***	0.025**
Panel B: Forecasting non-farm payroll growth rates						
Eurodollar	0.95	0.000***	0.374	0.97	0.000***	0.409
10-yr Treas.	1.07	0.000***	0.692	1.02	0.000***	0.559
30-yr Treas.	1.05	0.000***	0.630	1.10	0.000***	0.746
S&P 500	1.18	0.000***	0.890	1.30	0.000***	0.976
British pound	0.95	0.000***	0.340	1.10	0.000***	0.761
Japanese yen	1.11	0.000***	0.769	1.14	0.000***	0.813
Gold	1.01	0.000***	0.538	1.04	0.000***	0.650
WTI	0.96	0.000***	0.394	1.06	0.000***	0.684

Table 8: **Predicting the pre-FOMC stock drifts: In-sample evidence**

This table shows the in-sample predictive power of the steepening indicator for the pre-FOMC same-day returns (Panel A), overnight returns (Panel B), and 24-hour returns (Panel C). The pre-FOMC same-day return is defined as the return on the S&P 500 futures between 9:30 a.m. EST on the day of an FOMC announcement and 15 minutes before the announcement. The pre-FOMC overnight return is defined as the return on the S&P 500 futures between 24 hours before an FOMC announcement and 9:30 a.m. on the following FOMC day. The pre-FOMC 24-hour return is the sum of same-day and overnight returns. The sample period here spans from September 1997 to June 2020, restricted by the availability of the intraday S&P 500 futures data from Refinitiv Tick History. STEEP denotes the steepening indicator implied by speculators' positions in bond futures; TMSP denotes term spreads, the quarterly moving averages of the yield spreads between ten-year Treasury bonds and three-month Treasury bills; EBP denotes the bond excess premiums as calculated by Gilchrist and Zakrajšek (2012); and VIX denotes the Chicago Board of Options Exchange VIX index. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Constant	STEEP	VIX	TMSP	EBP	*adj.* R^2
Panel A: Forecasting the pre-FOMC same-day returns						
Reg. (1)	0.18***					0.0
	(3.15)					
Reg. (2)	-0.01	0.45***				13.8
	(-0.26)	(3.94)				
Reg. (3)	0.19		0.34	-0.06*	0.26***	18.0
	(1.55)		(0.51)	(-1.69)	(3.10)	
Reg. (4)	0.11	0.28***	0.14	-0.05*	0.21***	22.3
	(1.07)	(2.90)	(0.21)	(-1.71)	(2.85)	
Panel B: Forecasting the pre-FOMC overnight returns						
Reg. (1)	0.17**					0.0
	(2.35)					
Reg. (2)	0.08	0.22				0.2
	(1.54)	(1.07)				
Reg. (3)	0.03		2.18**	-0.17***	0.06	4.8
	(0.22)		(2.51)	(-2.63)	(0.43)	
Reg. (4)	0.02	0.03	2.16**	-0.17***	0.06	4.2
	(0.14)	(0.23)	(2.41)	(-2.61)	(0.40)	
Panel C: Forecasting the pre-FOMC 24-hour returns						
Reg. (1)	0.35***					0.0
	(3.20)					
Reg. (2)	0.07	0.67**				5.5
	(0.87)	(2.43)				
Reg. (3)	0.22		2.52***	-0.23***	0.32*	14.6
	(1.51)		(2.76)	(-3.31)	(1.87)	
Reg. (4)	0.13	0.32**	2.29***	-0.22***	0.26*	15.2
	(0.93)	(2.07)	(2.62)	(-3.36)	(1.68)	

Table 9: **Predicting the pre-FOMC stock drifts: Out-of-sample evidence and economic gains**

This table shows the out-of-sample forecasting power of the steepening indicator for the pre-FOMC same-day and overnight returns and its economic significance. The pre-FOMC same-day return is defined as the return on the S&P 500 futures between 9:30 a.m. EST on the day of an FOMC announcement and 15 minutes before the announcement. The pre-FOMC overnight return is defined as the return on the S&P 500 futures between 24 hours before an FOMC announcement and 9:30 a.m. on the following FOMC day. The sample period here spans from September 1997 to June 2020. I divide the sample period into two subperiods: the first in-sample estimation period (September 1997 to December 2002) and the out-of-sample evaluation period (January 2003 to June 2020). An out-of-sample R^2 is measured using a quadratic loss function and the Clark and West (2007) statistic is computed to test statistical significance. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The out-of-sample R^2 is further broken down into two subperiods, recessions and expansions, which are denoted by R^2_{Rec} and R^2_{Exp}, respectively. SR_{active} denotes the annualized Sharpe ratio of an active pre-FOMC timing strategy conditioned on the steepening indicator. SR_{naive} denotes the annualized Sharpe ratio of a naive pre-FOMC always-buy-and-sell strategy. ΔSR denotes a Sharpe ratio difference between the two strategies.

	Out-of-sample evidence				Economic significance		
Returns	R^2	Statistic	R^2_{Rec}	R^2_{Exp}	SR_{active}	SR_{naive}	ΔSR
Same-day	16.7	4.31***	25.9	12.5	1.059	0.694	0.36
Overnight	-1.9	0.65	0.8	-9.4	0.246	0.559	-0.31

Table 10: **Predicting the pre-FOMC stock drifts: Robustness**

This table tests if the predictive power of the steepening indicator for pre-FOMC same-day returns is robust to the asset market shocks during a lookback period leading up to the FOMC announcement as follows:

$$r_t^{sd} = \beta_0 + \beta_1 \text{STEEP}_{t-d} + \beta_2 \Delta\text{OIS}_{t-1|t-d} + \beta_3 \Delta\text{LIBOR}_{t-1|t-d} + \beta_4 \Delta\text{SPX}_{t-1|t-d} + \varepsilon_t,$$

where r_t^{sd} denotes the pre-FOMC same-day return, the lookback period (d) ranges from one week to two months, $\Delta\text{OIS}_{t-1|t-d}$ is a three-month overnight index swap (OIS) rate change between date $t-d$ and $t-1$, $\Delta\text{LIBOR}_{t-1|t-d}$ is a three-month LIBOR change between $t-d$ and $t-1$, and $\Delta\text{SPX}_{t-1|t-d}$ is a S&P index log return between $t-d$ and $t-1$. STEEP denotes the steepening indicator implied by speculators' positions in bond futures. The sample period here spans from September 1997 to June 2020, restricted by the availability of the intraday S&P 500 futures data from Refinitiv Tick History. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Constant	STEEP	ΔOIS	ΔLIBOR	ΔSPX	*adj.* R^2
Panel A: Lookback period = 1 week					
-0.01	0.44***	-1.53*	0.63	-1.98	16.3
(-0.12)	(3.99)	(-1.83)	(1.51)	(-1.15)	
Panel B: Lookback period = 2 weeks					
0.00	0.43***	0.29	-0.32	-3.15**	16.1
(0.04)	(3.83)	(0.54)	(-1.05)	(-2.21)	
Panel C: Lookback period = 1 month					
0.01	0.43***	-0.30	0.38	-2.40**	18.5
(0.22)	(3.83)	(-0.62)	(0.86)	(-2.44)	
Panel D: Lookback period = 2 months					
0.01	0.43***	-0.05	0.08	-1.27*	15.0
(0.17)	(3.79)	(-0.33)	(0.80)	(-1.77)	

Table 11: **Forecasting changes in Treasury yields: Out-of-sample evidence**

This table presents the out-of-sample forecasting power of the steepening indicator for monthly changes in Treasury yields with different maturities. A monthly yield change is defined as $\Delta y_t^T = y_t^T - y_{t-1}^T$, where y_t^T denotes the Treasury par yield with a maturity of T at the end of month t. Panels A, B, and C correspond to three benchmark models: the historical-average model, the model including term spreads, and the model including bond excess premiums. The sample spans from July 1986 to June 2020. Here, I divide the entire sample period into two subperiods: the first in-sample estimation period (July 1986–December 1999) and the out-of-sample evaluation period (January 2000–June 2020). The models are recursively estimated at each point in time throughout the out-of-sample evaluation period. The out-of-sample R^2 is measured using a quadratic loss function. The out-of-sample R^2 is further broken down into two subperiods, recessions and expansions, which are denoted by R^2_{Rec} and R^2_{Exp}, respectively. The McCracken (2007) test is applied to compare two nested models. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. $\overline{\beta}$ denotes an average of the coefficients on the steepening indicator over the out-of-sample evaluation period.

	1 month ahead					3 months ahead				
	$\overline{\beta}$	R^2	Statistic	R^2_{Rec}	R^2_{Exp}	$\overline{\beta}$	R^2	Statistic	R^2_{Rec}	R^2_{Exp}
Panel A: Constant + STEEP vs. Constant										
3-month Treasury	-0.14	9.4	2.03***	11.6	4.4	-0.13	7.8	1.69***	10.6	1.3
6-month Treasury	-0.11	8.3	2.09***	8.2	8.3	-0.14	9.4	1.69***	10.7	6.0
1-year Treasury	-0.09	5.9	1.83***	5.7	6.2	-0.15	9.1	1.60***	9.8	7.9
2-year Treasury	-0.06	1.9	1.02**	1.7	2.2	-0.15	5.7	1.33***	5.3	6.4
5-year Treasury	-0.01	-0.9	-1.71	-0.7	-1.3	-0.11	1.5	0.64*	1.3	1.8
10-year Treasury	0.03	-1.2	-2.24	-0.8	-2.0	-0.07	0.2	0.16	-0.1	0.7
20-year Treasury	0.03	-0.9	-1.39	-0.3	-2.0	-0.05	-0.1	-0.12	-0.5	0.7
Panel B: Constant + STEEP + TMSP vs. Constant + TMSP										
3-month Treasury	-0.13	9.3	2.28***	11.4	4.6	-0.13	8.2	2.04***	10.6	2.6
6-month Treasury	-0.10	8.2	2.22***	8.1	8.2	-0.14	9.9	1.99***	10.8	7.5
1-year Treasury	-0.09	5.7	1.90***	5.8	5.6	-0.15	9.5	1.81***	9.9	8.8
2-year Treasury	-0.06	1.8	1.01**	1.8	1.6	-0.14	5.8	1.39***	5.3	6.6
5-year Treasury	-0.01	-0.9	-1.70	-0.7	-1.4	-0.11	1.5	0.61*	1.3	1.8
10-year Treasury	0.02	-1.2	-2.28	-0.8	-1.9	-0.07	0.2	0.15	-0.0	0.6
20-year Treasury	0.03	-0.9	-1.46	-0.4	-1.9	-0.05	-0.1	-0.12	-0.5	0.6
Panel C: Constant + STEEP + EBP vs. Constant + EBP										
3-month Treasury	-0.10	5.3	1.92***	5.9	4.1	-0.10	5.4	1.66***	6.6	2.7
6-month Treasury	-0.06	3.6	1.68***	2.6	5.7	-0.11	6.1	1.54***	6.0	6.3
1-year Treasury	-0.04	2.0	1.24**	1.2	3.2	-0.13	6.0	1.41***	5.2	7.4
2-year Treasury	-0.01	0.0	0.01	-0.1	0.2	-0.13	4.2	1.22**	2.9	6.0
5-year Treasury	0.03	-0.9	-1.98	-0.6	-1.6	-0.11	1.3	0.60*	0.4	3.0
10-year Treasury	0.05	-0.5	-0.75	0.4	-2.3	-0.08	0.2	0.13	-0.8	2.0
20-year Treasury	0.05	-0.4	-0.50	0.8	-2.6	-0.06	0.0	0.02	-0.9	1.8

Table 12: **Forecasting changes in the slope of the yield curve: Out-of-sample evidence**

This table presents the out-of-sample forecasting power of the steepening indicator for monthly changes in the slope of the Treasury yield curve. A slope change is defined as a monthly change in the yield spread between T-year Treasury bond and three-month Treasury bill. Panels A, B, and C correspond to three benchmark models: the historical-average model, the model including term spreads, and the model including bond excess premiums. The sample spans from July 1986 to June 2020. Here, I divide the entire sample period into two subperiods: the first in-sample estimation period (July 1986–December 1999) and the out-of-sample evaluation period (January 2000–June 2020). The models are recursively estimated at each point in time throughout the out-of-sample evaluation period. The out-of-sample R^2 is measured using a quadratic loss function. The out-of-sample R^2 is further broken down into two subperiods, recessions and expansions, which are denoted by R^2_{Rec} and R^2_{Exp}, respectively. The McCracken (2007) test is applied to compare two nested models. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. $\overline{\beta}$ denotes an average of the coefficients on the steepening indicator over the out-of-sample evaluation period.

	1 month ahead					3 months ahead				
	$\overline{\beta}$	R^2	Statistic	R^2_{Rec}	R^2_{Exp}	$\overline{\beta}$	R^2	Statistic	R^2_{Rec}	R^2_{Exp}
Panel A: Constant + STEEP vs. Constant										
10-year Treasury	0.16	4.6	1.94***	8.8	2.9	0.06	1.0	0.84**	2.1	0.5
15-year Treasury	0.17	5.3	2.08***	9.2	3.5	0.08	1.6	1.16**	3.4	0.8
20-year Treasury	0.17	5.8	2.15***	10.0	3.9	0.09	2.0	1.27**	4.1	1.0
25-year Treasury	0.17	6.4	2.23***	10.8	4.4	0.09	2.3	1.39***	4.4	1.3
30-year Treasury	0.18	6.9	2.30***	11.7	4.9	0.09	2.5	1.53***	4.6	1.7
Panel B: Constant + STEEP + TMSP vs. Constant + TMSP										
10-year Treasury	0.16	4.6	2.40***	8.1	3.1	0.06	1.0	1.02**	1.7	0.7
15-year Treasury	0.16	5.2	2.58***	8.6	3.7	0.07	1.7	1.39***	3.0	1.1
20-year Treasury	0.16	5.7	2.67***	9.3	4.1	0.08	2.1	1.51***	3.6	1.4
25-year Treasury	0.17	6.3	2.77***	10.2	4.6	0.08	2.4	1.62***	3.9	1.7
30-year Treasury	0.17	6.8	2.86***	11.0	5.1	0.08	2.6	1.76***	4.1	2.0
Panel C: Constant + STEEP + EBP vs. Constant + EBP										
10-year Treasury	0.15	3.9	2.14***	5.7	3.1	0.02	0.1	0.09	-0.2	0.2
15-year Treasury	0.14	4.1	2.16***	5.4	3.4	0.04	0.5	0.66*	0.4	0.5
20-year Treasury	0.14	4.2	2.16***	5.3	3.7	0.04	0.6	0.74**	0.5	0.7
25-year Treasury	0.14	4.5	2.18***	5.3	4.1	0.04	0.7	0.76**	0.4	0.8
30-year Treasury	0.15	4.8	2.21***	5.4	4.6	0.04	0.7	0.78**	0.1	1.0

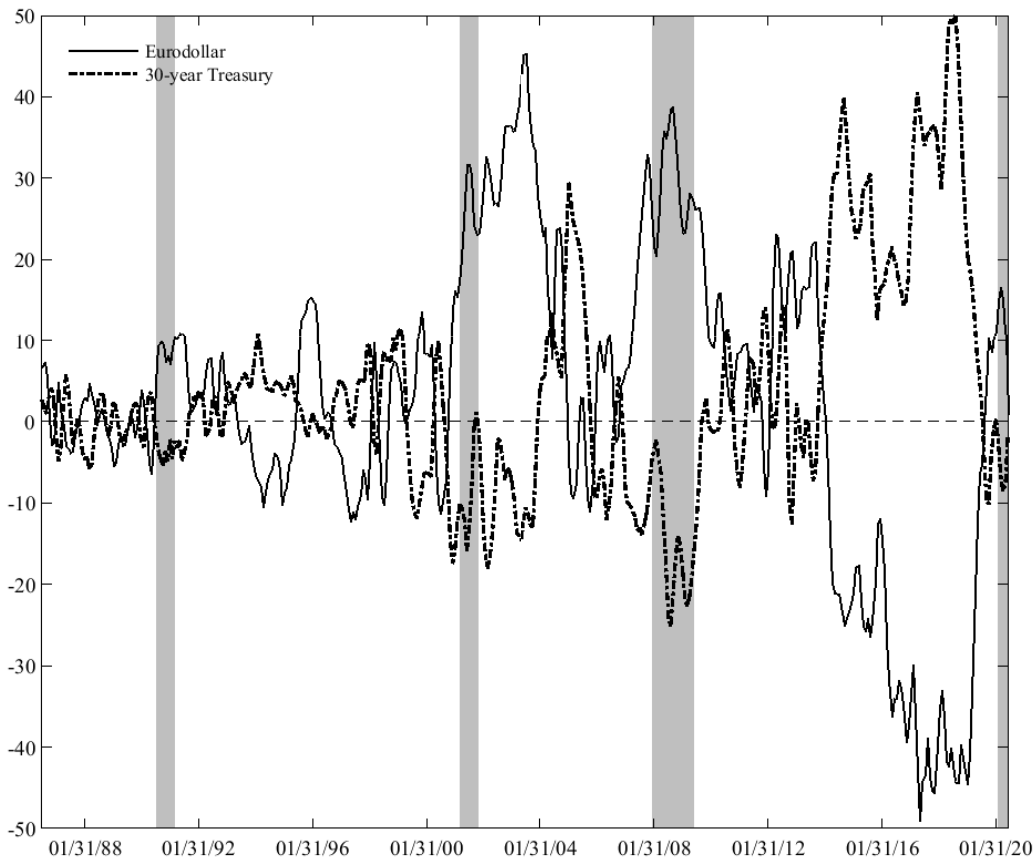


Figure 1: Time series of the excess net number of speculators in bond futures. The solid and dotted lines correspond to Eurodollar futures and 30-year Treasury futures, respectively. The sample spans from July 1986 to June 2020. The shaded areas refer to the four NBER-designated recessions included in the sample period.

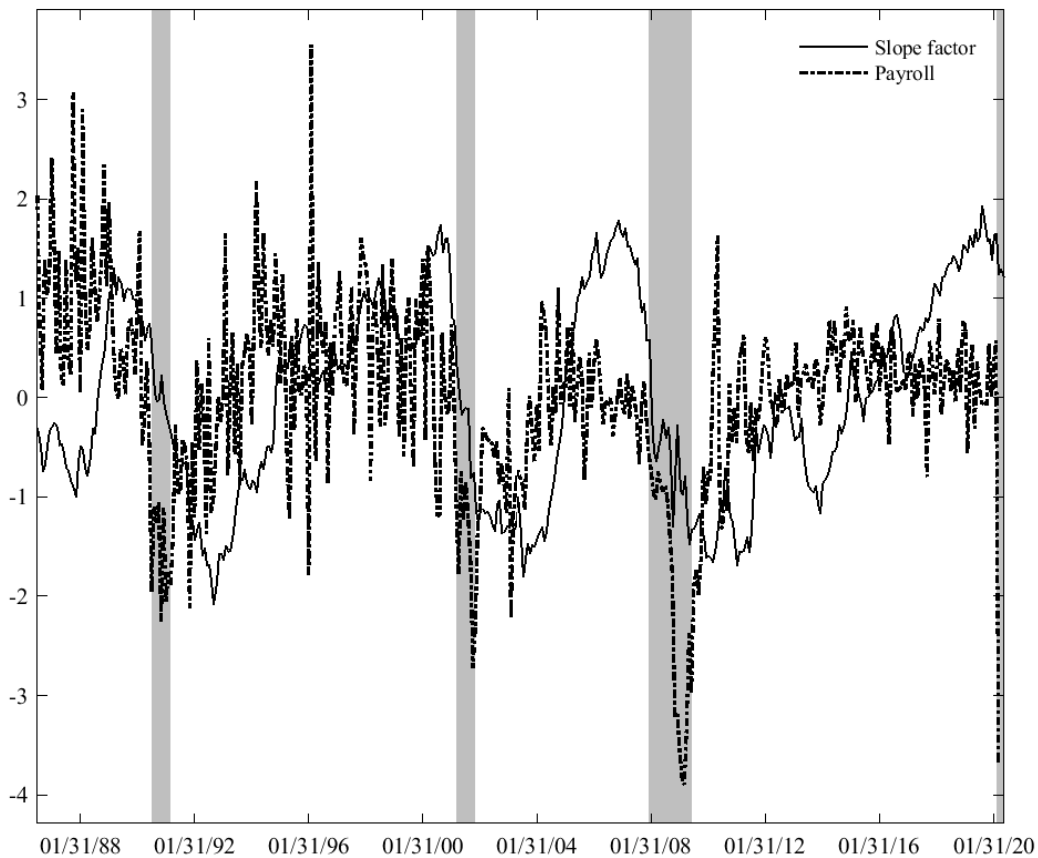
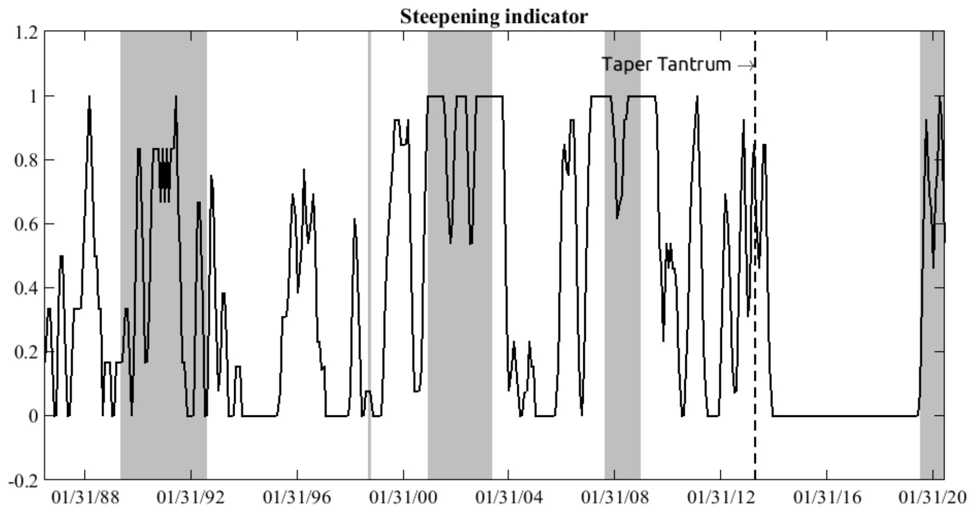


Figure 2: Time series of the slope of the yield curve and the non-farm payroll growth rate. The slope factor (solid line) is the second principal component of a cross-section of Treasury yields with maturities from 1 to 30 years for the period from July 1986 to June 2020. The first-release vintage data on non-farm payroll growth rates (dotted line) are obtained from the Federal Reserve Bank of Philadelphia for the period from July 1986 to March 2020. Note that both time series are standardized for comparison and that I drop the recent three months (April through June 2020) for payroll growth rates because of their astronomical levels. The shaded areas refer to the four NBER-designated recessions.



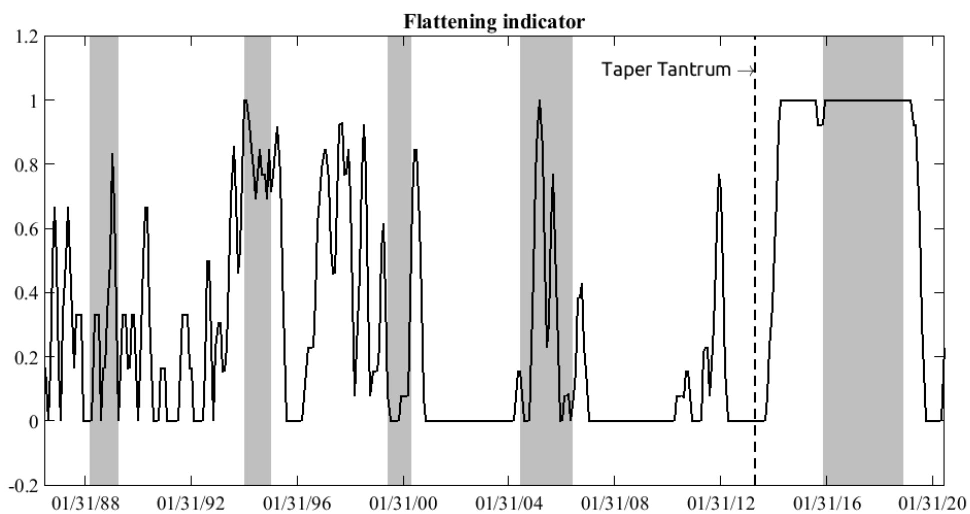


Figure 3: Time series of the spreading indicators. Panel A shows the time series of the steepening indicator, with the shaded areas referring to the five easing episodes included in my sample: (i) June 6, 1989 to September 4, 1992; (ii) September 29, 1998 to November 17, 1998; (iii) January 3, 2001 to June 25, 2003; (iv) September 18, 2007 to January 28, 2009; and (v) August 1, 2019 to the sample-end. Panel B shows the time series of the flattening indicator, with the shaded areas referring to the five tightening episodes included in my sample: (i) March 30, 1988 to May 4, 1989; (ii) February 4, 1994 to February 1, 1995; (iii) June 30, 1999 to May 16, 2000; (iv) June 30, 2004 to June 29, 2006; and (v) December 17, 2015 to December 20, 2018. The vertical dotted line refers to the taper tantrum in May 2013 when former Chairman Ben Bernanke first indicated a slowdown of quantitative easing in testimony before the Joint Economic Committee.

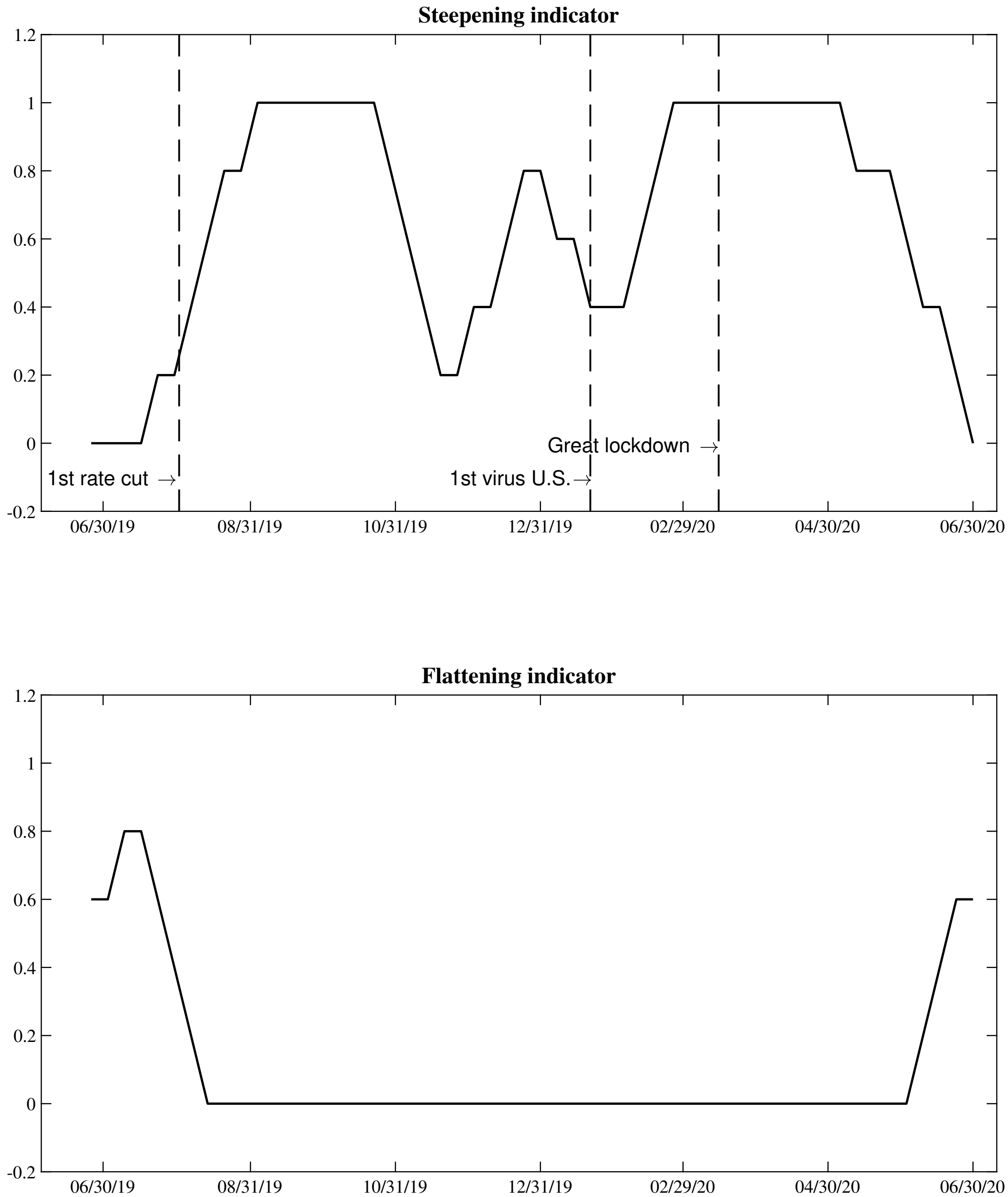


Figure 4: Evolution of the spreading indicators around the coronavirus pandemic. The three vertical lines refer to the first policy rate cut in the ongoing easing cycle that began on August 1, 2019; the first corona virus case in the United States on January 21, 2020; and the March 15 Great Lockdown when 33 states and the District of Columbia closed their public schools. Here, to provide a more vivid change, I calculate the spreading indicators at a weekly frequency using one-month (but not three-month) moving averages.

Appendix A Additional Empirical Results

Appendix A.1 Predicting payroll growth using the positions of large hedgers and small investors

I here examine whether large hedgers and small investors have predictive information about future payroll growth rates, similar to large speculators. To this end, I re-define the spreading indicators using their positions data on bond futures, similar to Equations (2) and (3). I then run the predictive regression of spreading indicators for h-month-ahead payroll growth rates similar to Equation (6).

Table A.1 shows the predictive regression results. Panels A and B correspond to the results using the data on large hedgers and small players, respectively. Note that large hedgers' spreading indicators have no predictive power for future payroll growth rates regardless of forecast horizons. In contrast, small players' spreading indicators have predictive power for future payroll growth rates up to six months ahead at the 1% level. Importantly, small players' steepening and flattening indicators have positive and negative relations to future payroll growths, respectively. This result suggests that small players have bet on the slope of the yield curve in the wrong direction, meeting the net demand from large speculators.

Appendix A.2 Predicting volatility spreads

Authors such as Cremers and Weinbaum (2010), Jin, Livnat, and Zhang (2012), and Chan, Ge, and Lin (2015) find that option volatility spreads (the differences between put- and call-implied volatilities) have predictive power for stock returns because of informed trading in options markets. It is possible that the information contained in spread trades is revealed in stock index options market at the market close just before future payroll releases. To test such a possibility, I examine the predictive power of spreading indicators for volatility spreads on the days surrounding future payroll releases by running the following predictive regression:

$$\text{VS}_{t+h-d} = \alpha + \beta \text{SPRD}_t + \varepsilon_{t+h-d},$$

where VS_{t+h-d} denotes the volatility spread observed d days before the h-month-ahead payroll release and SPRD_t denotes either the steepening indicator or the flattening indicator. The volatility spread is calculated using the closing prices of the most at-the-money (ATM) put-call pair with the same strike price and the same nearest maturity.[18] The options data range from January 1996 to December 2017 and come from OptionMetrics.

Panel A of Table A.2 shows the prediction results for volatility spreads at the market close just before future payroll releases ($d = 1$). The coefficient on STEEP is positive at the 5% level, implying that a higher value of STEEP is associated with a higher volatility spread at the market close just before future payroll releases. The coefficient on FLAT is negative at the 5% level, implying that a higher value of FLAT is associated with a lower volatility spread at the market close just before future payroll releases. The signs are consistent with the argument that steepening (flattening) indicators may have negative (positive) information about future economic activity.

Panels B and C show the prediction results for volatility spreads when $d = 2$ and $d = 0$, respectively. There is no similar predictive power two days before future payroll releases ($d = 2$) or the very days of future payroll releases ($d = 0$). Overall, my results suggest that some informed traders attempt to time the stock market using stock index options at the market close just before payroll announcements.

Appendix A.3 Predicting pre-FOMC same-day returns with various lookback periods

I here examine whether the predictive power of the steepening indicator for the pre-FOMC same-day return is robust to the choice of a lookback period. To do so, I re-run the predictive

[18] The results generally become weaker with non-ATM options and longer-dated options.

regression as in Equation (12) with various lookback periods.

Table A.3 shows the in-sample forecasting power of the steepening indicator for the pre-FOMC same-day returns. The explanatory variables are observed with a lookback period of one week (Panel A), one month (Panel B), and two months (Panel C). Note that the steepening indicator has very similar coefficients across different lookback periods. The statistical significance is obtained at the 1% level regardless of lookback periods without control variables and at the 1% to 5% level with control variables.

Table A.1: **Predicting payroll growth rates using the positions of large hedgers and small investors**

This table shows the in-sample forecasting power of spreading indicators for payroll growth rates using the positions of large hedgers (Panel A) and small investors (Panel B). STEEP denotes the steepening indicator implied by hedgers' or small players' positions in bond futures; FLAT denotes the flattening indicator implied by hedgers' or small players' positions in bond futures; TMSP denotes term spreads, the quarterly moving averages of the yield spreads between ten-year Treasury bonds and three-month Treasury bills; EBP denotes the bond excess premiums as calculated by Gilchrist and Zakrajšek (2012); and FFR denotes real federal fund rates, the differences between the effective federal fund rates and the inflation rates as implied by the core PCE price index. The sample spans from July 1986 to March 2020. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	STEEP as a predictor				FLAT as a predictor		
	3 months ahead	6 months	12 months		3 months ahead	6 months	12 months
Panel A: Large hedgers							
STEEP	-0.30	-0.41	0.67	FLAT	0.50*	0.53*	0.18
	(-0.65)	(-0.63)	(1.22)		(1.83)	(1.74)	(0.44)
TMSP	0.21**	0.36***	0.49***	TMSP	0.20*	0.35***	0.54***
	(2.01)	(3.13)	(2.97)		(1.92)	(3.05)	(3.22)
EBP	-0.56***	-0.61***	-0.53***	EBP	-0.58***	-0.64***	-0.46***
	(-4.49)	(-5.03)	(-3.46)		(-4.32)	(-4.71)	(-2.85)
FFR	0.28**	0.30**	0.07	FFR	0.24*	0.25*	0.12
	(2.05)	(2.00)	(0.50)		(1.95)	(1.89)	(0.99)
Lagged	0.68***	0.48***	0.34**	Lagged	0.66***	0.46***	0.32**
	(5.71)	(4.14)	(2.38)		(5.55)	(4.00)	(2.19)
Const.	0.29	0.16	-0.08	Const.	0.10	-0.05	-0.13
	(1.30)	(0.64)	(-0.20)		(0.42)	(-0.17)	(-0.27)
adj. R^2	37.3	30.3	19.1	*adj.* R^2	38.0	31.0	18.4
NOBS	402	399	393	NOBS	402	399	393
Panel B: Small players							
STEEP	0.80***	0.84***	0.58*	FLAT	-1.16***	-1.39***	-0.80*
	(3.80)	(3.40)	(1.89)		(-4.11)	(-3.09)	(-1.73)
TMSP	0.24**	0.40***	0.58***	TMSP	0.21**	0.37***	0.55***
	(2.47)	(3.59)	(3.40)		(2.27)	(3.64)	(3.48)
EBP	-0.57***	-0.63***	-0.45***	EBP	-0.45***	-0.48***	-0.36**
	(-4.25)	(-4.75)	(-2.85)		(-3.31)	(-4.22)	(-2.35)
FFR	0.33**	0.35**	0.19	FFR	0.33**	0.36**	0.18
	(2.49)	(2.40)	(1.35)		(2.52)	(2.49)	(1.33)
Lagged	0.58***	0.37***	0.25*	Lagged	0.56***	0.33**	0.24
	(4.74)	(3.23)	(1.67)		(4.51)	(2.47)	(1.55)
Const.	-0.08	-0.25	-0.34	Const.	0.61***	0.52**	0.16
	(-0.31)	(-0.80)	(-0.70)		(2.88)	(2.04)	(0.42)
adj. R^2	39.9	33.1	19.7	*adj.* R^2	40.2	34.5	19.8
NOBS	402	399	393	NOBS	402	399	393

Table A.2: **Predicting volatility spreads**

This table tests if spreading indicators can predict volatility spreads (the difference between the put- and call-implied volatilities) on the days surrounding future payroll releases:

$$\mathrm{VS}_{t+h-d} = \alpha + \beta \mathrm{SPRD}_t + \varepsilon_{t+h-d},$$

where VS_{t+h-d} denotes the volatility spread observed d days before the h-month-ahead payroll release and SPRD_t denotes either the steepening indicator or the flattening indicator. The volatility spread is calculated using the closing prices of the most at-the-money put-call pair with the same strike price and the same nearest maturity. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	STEEP as a predictor				FLAT as a predictor		
	$h=1$ month	2 months	3 months		$h=1$ month	2 months	3 months
Panel A: The day before payroll announcements ($d=1$)							
STEEP	0.50**	0.50**	0.47**	FLAT	-0.40**	-0.40**	-0.36**
	(2.52)	(2.46)	(2.24)		(-2.49)	(-2.57)	(-2.09)
Const.	-0.05	-0.06	-0.04	Const.	0.29***	0.28***	0.27***
	(-0.53)	(-0.54)	(-0.38)		(2.68)	(2.74)	(2.60)
adj. R^2	1.4	1.4	1.1	*adj.* R^2	0.7	0.7	0.5
NOBS	259	258	257	NOBS	259	258	257
Panel B: Two days before payroll announcements ($d=2$)							
STEEP	-0.11	-0.07	-0.17	FLAT	0.06	0.06	0.17
	(-0.61)	(-0.40)	(-0.92)		(0.32)	(0.35)	(0.89)
Const.	0.33***	0.31***	0.35***	Const.	0.27***	0.26***	0.23***
	(3.57)	(3.38)	(3.35)		(2.75)	(2.77)	(2.63)
adj. R^2	-0.3	-0.3	-0.1	*adj.* R^2	-0.4	-0.4	-0.2
NOBS	258	257	256	NOBS	258	257	256
Panel C: The payroll announcement days ($d=0$)							
STEEP	-0.15	-0.34	-0.46	FLAT	-0.08	0.11	0.34
	(-0.46)	(-0.95)	(-1.04)		(-0.22)	(0.43)	(0.88)
Const.	0.17	0.26	0.30	Const.	0.13	0.08	-0.01
	(0.97)	(0.90)	(0.87)		(0.45)	(0.36)	(-0.03)
adj. R^2	-0.3	-0.1	0.0	*adj.* R^2	-0.4	-0.4	-0.2
NOBS	253	252	251	NOBS	253	252	251

Table A.3: **Predicting the pre-FOMC same-day drifts with various lookback periods**

This table shows the in-sample predictive power of the steepening indicator for the pre-FOMC same-day returns. The pre-FOMC same-day return is defined as the return on the S&P 500 futures between 9:30 a.m. EST on the day of an FOMC announcement and 15 minutes before the announcement. The explanatory variables are observed with a lookback of one week (Panel A), one month (Panel B), and two months (Panel C). The sample period here spans from September 1997 to June 2020, restricted by the availability of the intraday S&P 500 futures data from Refinitiv. STEEP denotes the steepening indicator implied by speculators' positions in bond futures; TMSP denotes term spreads, the quarterly moving averages of the yield spreads between ten-year Treasury bonds and three-month Treasury bills; EBP denotes the bond excess premiums as calculated by Gilchrist and Zakrajšek (2012); and VIX denotes the Chicago Board of Options Exchange VIX index. Newey and West (1987) robust t-statistics with an optimal lag are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Constant	STEEP	VIX	TMSP	EBP	*adj.* R^2
Panel A: Lookback period = one week						
Reg. (1)	0.18***					-0.0
	(3.18)					
Reg. (2)	-0.02	0.47***				15.5
	(-0.40)	(4.19)				
Reg. (3)	-0.02		1.38**	-0.05*	0.18**	22.6
	(-0.18)		(2.37)	(-1.72)	(2.36)	
Reg. (4)	-0.09	0.28***	1.14**	-0.05*	0.14**	26.8
	(-0.90)	(3.03)	(1.98)	(-1.88)	(1.98)	
Panel B: Lookback period = one month						
Reg. (1)	0.18***					-0.0
	(3.18)					
Reg. (2)	-0.00	0.43***				13.2
	(-0.09)	(3.87)				
Reg. (3)	0.24*		0.05	-0.05*	0.28***	17.2
	(1.90)		(0.08)	(-1.71)	(3.52)	
Reg. (4)	0.15	0.28***	-0.09	-0.05*	0.22***	21.4
	(1.46)	(2.92)	(-0.15)	(-1.76)	(3.22)	
Panel C: Lookback period = two months						
Reg. (1)	0.18***					-0.0
	(3.18)					
Reg. (2)	0.01	0.42***				12.1
	(0.11)	(3.61)				
Reg. (3)	0.12		0.78	-0.06*	0.20**	16.4
	(0.94)		(1.21)	(-1.82)	(2.52)	
Reg. (4)	0.05	0.26**	0.58	-0.06*	0.16**	20.0
	(0.45)	(2.55)	(0.98)	(-1.85)	(2.16)	