Spread Trades, Business Cycles, and Asset Prices

Yang-Ho Park

Federal Reserve Board

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ABSTRACT

The slope of the yield curve is closely linked to the real economy and monetary policy. I find that speculators' spread positions in bond futures can predict subsequent non-farm payroll "surprises," the differences between actual payroll data and analysts' forecasts. Furthermore, spread trading can forecast intraday bond returns at the times of subsequent payroll data releases and stock returns in anticipation of FOMC announcements (also known as the pre-FOMC drift). These results suggest that some investors have private information about business cycles and monetary policies.

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1 Introduction

Asymmetric information is an essential friction in understanding investors' behavior and asset prices. Although private information is taken for granted in finance theory, it is an important empirical question whether or not sophisticated investors have superior information acquisition and processing ability. It is also important to understand how private information, if any, gets incorporated into asset prices. This paper provides evidence for informed speculation about business cycle fluctuations and examines its implications for asset prices.

The key idea of this paper is that spread trade in bond futures has potential as a prime business-cycle strategy, where spread trade refers to a purchase of one bond future and a simultaneous sale of another bond future with a different maturity. This idea is based on the stylized fact that the slope of the yield curve has a close relationship to the real economy and monetary policy (see Diebold, Rudebusch, and Aruoba 2006; Gürkaynak, Sack, and Swanson 2005; and Rudebusch and Wu 2008). Curve steepening trade can be useful right before or during a recession in which short-term rates tend to drop faster than long-term rates. Conversely, curve flattening trade can be useful when investors anticipate a monetary tightening in which short-term rates tend to rise faster than long-term rates. Therefore, if some investors have private information about the business cycle, such information may manifest itself in their spread positions.

It should be noted that, compared to outright trade, spread trade has two appealing features as an informed trading strategy: low risk and low cost. Above all, spread trade is largely shielded from any parallel shift in the term structure of interest rates. In particular, a duration-matched spread trade can be useful when investors are informed about real economic activity but uncertain about more permanent shocks, such as inflation and productivity shocks, which tend to affect yields more evenly across all maturities. In addition, the prior literature shows that the leverage of a security is a crucial determinant of its informational role because high leverage can facilitate informed traders to lever their informational advantage (see Black 1975; and Easley, O'Hara, and Srinivas 1998). Importantly, spread trade is subject to lower margin requirements than outright trade, so spread trading may be preferred as an informed trading strategy to directional trading.

Using the Commitments-of-Traders (COT) data from July 1986 to July 2017, I find that speculators as a group took the correct positions on the slope of the yield curve along different phases of the business cycle. Specifically, speculators' spread positions have predictive information about the National Bureau of Economic Research (NBER)-designated recessions, with a stronger steepening (flattening) position associated with a higher (lower) probability of subsequent recessions. In addition, spread positions are predictive of subsequent non-farm payroll growth rates, which are closely watched by traders and policy makers. The predictive power of spread positions is particularly strong during recessions rather than during expansions, implying that speculators are good at assessing economic fundamentals in difficult times. Moreover, all of these results survive the inclusion of other business-cycle indicators such as term spreads (Estrella and Hardouvelis 1991) and bond excess premiums (Gilchrist and Zakrajšek 2012). Overall, speculators' spread positions have robust predictive power for the business cycle.

One may argue that the forecasting power of spread positions does not necessarily mean that speculators have private information about the business cycle. It is possible that speculators' superior ability to time the slope of the yield curve is based on some macroeconomic or financial variables that may have causal effects on the real economy. If this was the case, it would be difficult to tease out whether the predictive power of spread positions is due to private information *per se* or the causal effect of the underlying information. I find, however, that spread positions have the unique ability to predict non-farm payroll surprises (the differences between actual payroll announcements and analysts' forecasts) in subsequent months. This finding suggests that speculators have some information that has not been accounted for by analysts, thereby challenging the traditional assumption that analysts provide an efficient forecast of macroeconomic variables.

Turning to the information content of spread trade for asset prices, I find that speculators' spread positions can predict a significant fraction of the variation in the term structure of interest rates. Specifically, a stronger steepening position is followed by a decrease in short-term Treasury yields and an increase in the slope of the Treasury yield curve in subsequent months. More strikingly, spread positions can forecast the immediate response of short-term bond future prices to non-farm payroll announcements a few months before the payroll data releases. This finding is consistent with the earlier result that spread positions can forecast non-farm payroll surprises, and further supports my argument that speculators' spread positions contain private information about the business cycle.

Spread positions have predictive information about stock returns as well. Recently, Lucca and Moench (2015) document that about 80% of the excess returns on the S&P 500 stock index had accumulated during the 24-hour windows immediately preceding scheduled Federal Open Market Committee (FOMC) announcements, a finding referred to as the pre-FOMC drift. While the authors argue that the pre-FOMC drift is difficult to reconcile with standard asset pricing theory, I find that spread positions can forecast the pre-FOMC stock returns. Furthermore, if the predictable component associated with spread positions is excluded from the pre-FOMC stock returns, the residual unpredictable component is no longer statistically different from zero, suggesting that the pre-FOMC drift may be spurious. A potential explanation for these results is that speculators engage in informed trading in stock markets right before policy announcements and that the pre-FOMC drift is driven by such informed speculation about soon-to-be-announced policy decisions.

My findings have a policy implication. Recent studies documents the possibility of information leakage about the FOMC and macroeconomic news announcements. Bernile, Hu, and Tang (2016) find that the S&P 500 futures' abnormal order imbalances ahead of FOMC announcements move in a way that is aligned with subsequent policy surprises. Kurov, Sancetta, Strasser, and Wolfe (2017) discover similar evidence for informed trading right before several macroeconomic news announcements. However, my paper documents that speculators' spread positions can predict the financial market responses on the days of non-farm payroll and FOMC announcements a few months ahead of the news releases. This result suggests that some speculators may have a better ability to process macroeconomic information and engage in speculative informed trading right before the release of the information. Thus, the existence of a pre-announcement drift does not necessarily indicate information leakage.

This paper adds to the vast literature that identifies business-cycle indicators from financial markets. For example, Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) find that the slope of the yield curve is a harbinger of recessions, and Gilchrist and Zakrajšek (2012) document that credit spreads are a leading indicator of the business cycle. Ang, Piazzesi, and Wei (2006) argue that short-term rates are more informative about gross domestic product (GDP) growth than term spreads. Market uncertainty and liquidity measures also have predictive information for the business cycle (see Bloom 2009; Bekaert and Hoerova 2014; and Næs, Skjeltorp, and Ødegaard 2011). However, these widely accepted indicators are considered to have some causal effects on the real economy, so their predictability does not necessarily mean that some traders have private information about the real economy. In contrast, my analysis provides more convincing evidence for informed trading by predicting non-farm payroll surprises and bond market responses at the times of non-farm payroll data releases.

Finally, this paper contributes 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 private information about the business cycle plays an important role in explaining changes in the short end and slope of the yield curve.

The rest of the paper is organized as follows: Section 2 introduces spread trade in bond futures and its identification; Section 3 examines the information content of spread trade for the business cycle; Section 4 investigates the implications of spread trade for bond and stock prices; and Section 5 concludes.

2 Spread trade and its identification

2.1 Spread trade as a business-cycle strategy

Spread trade 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 that they have. For example, suppose that you have a better ability to forecast a category-five hurricane which might 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. However, such a position would expose yourself to the risks that have little to do with hurricane, such as oil demand in China and political uncertainty in the Middle East. Instead, spread trade between the WTI and Brent crude oil futures would expose you only to the hurricane risk, eliminating other risks that are common to both oil prices.

I conjecture that private information about real economic activity, if any, may manifest itself in spread trade in bond futures. This conjecture is based on the stylized fact that the slope of the yield curve is closely linked to real economic activity (see Diebold, Rudebusch, and Aruoba 2006). Figure 1 illustrates such a tight link between the non-farm payroll growth rate (a key business-cycle variable) 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 from 1 to 30 years.

Furthermore, the slope of the yield curve sharply responds to monetary policy shocks (see Gürkaynak, Sack, and Swanson 2005; and Rudebusch and Wu 2008). Figure 2 presents the evolution of the term structure during two episodes of the monetary cycle. Panel A of the figure demonstrates that the slope of the yield curve tends to steepen during an easing cycle by comparing the term structure on January 3, 2001 (the starting date of a monetary easing) to the term structure one year later. Panel B of the figure demonstrates that the slope of the yield curve tends to flatten during a tightening cycle by comparing the term structure on June 30, 2004 (the starting date of a monetary tightening) to the term structure one year later.

Given such empirical regularities, investors may profit from playing the slope of the yield curve when informed about business and monetary cycles. For example, increasing holdings of short-term bonds relative to long-term bonds (referred to as curve steepening) can be useful right ahead of an imminent recession or monetary easing. Conversely, reducing holdings of short-term bonds relative to long-term bonds (referred to as curve flattening) can be useful at the peak of the business cycle or ahead of a monetary tightening.

Of course, 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 often rise faster than short-term rates. 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. Furthermore, in the past decade, central banks have increasingly relied on forward guidance and quantitative easing, and such non-conventional monetary policies may have different implications for the slope of the yield curve than conventional ones. Nevertheless, other factors have, on average, less of an influence on the slope of the yield curve than business-cycle risk.

2.2 Identifying spread trade

Informed spread trading is identified using the futures-only version of the Legacy COT data published by the Commodity Futures Trading Commission (CFTC).[1] The data contain the 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 sample spans from July 1986 to July 2017.

In particular, I focus on the net number of speculators, the difference between the numbers of long and short speculators, for three of the most liquid bond futures: Eurodollar (ticker=ED), ten-year Treasury (TY), and 30-year Treasury (US). I do not use other bond futures, such as federal funds (FF), two-year Treasury (TU), and five-year Treasury (FV), because the COT data on these bond futures are unavailable in the beginning of the sample period. In addition, although federal funds futures substantially grew in recent years, their trading volume is still one-order-of-magnitude smaller than that of Eurodollar futures.

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. First, I compute an equally weighted average of the net speculators over the three selected futures: $\overline{\mathrm{SP}}_t = \frac{1}{3}\sum_{i\in\{3M,10Y,30Y\}} \mathrm{SP}_t^i$. I then compute the *excess* net number of speculators in each market by subtracting the average net number of speculators from

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

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. The excess net number of speculators in a given future is indicative of speculators' view as a group on its performance relative to the overall performance of bond futures. For example, if EXSP_t^{3M} is positive, it means that speculators are expecting Eurodollar futures to outperform the other bond futures overall.

Figure 3 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 three NBER-designated recessions included in my sample period. A striking feature emerging from the figure is that 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. 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 almost all of the recession periods. With these noted, speculators as a group appear to have bet on a reduction in short-term rates relative to long-term rates ahead of and throughout recessions.

I now define a steepening indicator based on the signs of the excess net numbers of speculators in bond futures. Specifically, I introduce a binary variable which takes one if the excess net number of speculators is positive in Eurodollar futures (the short end of the yield curve) and negative in 30-year Treasury futures (the long end of the yield curve) and is zero otherwise. The steepening indicator is then defined as a quarterly moving average of the binary variable:

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

where STEEP_t denotes the steepening indicator at time t, q stands for quarter, and N_t denotes the number of COT data observations over the past quarter. A high value of STEEP_t is associated with speculators' expectation that the yield curve may become steeper in subsequent periods.

Similarly, I introduce another binary variable which takes one if the excess net number of speculators is negative in Eurodollar futures and positive in 30-year Treasury futures and is zero otherwise. The 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' expectation that the yield curve may become flatter in subsequent periods.

Panel A of Figure 4 shows the time-evolution of the steepening indicator, where the shaded areas refer to the four 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, the one beginning in September 1998. Furthermore, the steepening indicator reached its peaks before the start of easing cycles in two instances: the ones starting in January 2001 and September 2007.

Panel B of Figure 4 shows the time-evolution of the flattening indicator, where the shaded areas refer to the five tightening episodes included in my sample period. This chart shows that, 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 three of tightening episodes: the ones starting in February 1994, June 2004, and December 2015. In particular, speculators switched to and maintained the strongest flattening view of the term structure after the so-called taper tantrum in May 2013 when former Chairman Ben Bernanke first indicated a slowdown of quantitative easing in testimony before the Joint Economic Committee.

3 Spread trade and the business cycle

This section examines the information content of spread positions for recession probabilities and non-farm payroll growth rates. I also compare the predictive power of spread trade to that of outright trade in various futures markets and discuss the private nature of the information contained in spread positions.

3.1 Forecasting recession probabilities

Let SPRD_t denote a spread indicator, which refers to either STEEP_t or FLAT_t. To examine the information content of the spread indicator, I 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 which takes one if the $t + h$ month is declared to be a recession month and zero otherwise. Here, z_t denotes a vector of control variables, including term spreads (TMSP), bond excess premiums (EBP), and real federal fund rates (FFR). Term spreads are defined as quarterly moving averages of the yield spreads between ten-year Treasury bonds and three-month Treasury bills; bond excess premiums are a measure of credit risk premiums provided by Gilchrist and Zakrajšek (2012); and real federal fund rates 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.

Table 1 provides the summary statistics of and the correlation matrix among the explanatory variables. The table shows that STEEP and FLAT are positively and negatively correlated with EBP, respectively, suggesting that spread positions and bond excess premiums share some common information. In contrast, STEEP and FLAT both are weakly correlated with TMSP, indicating that spread positions may have very different information from the slope of the yield curve.

Panel A of Table 2 shows the in-sample Probit regression results. The table shows that a higher value of STEEP is associated with a higher probability of recession in subsequent months. The statistical significance of STEEP is obtained at the 1% level in three- and six-month-ahead forecasting and at the 5% level in 12-month-ahead forecasting. 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 5% level in three- and six-month-ahead forecasting. Note that these results are obtained after the inclusion of control variables, suggesting that the spread indicators contain distinct information about future recession probabilities from traditional predictors.

To assess the out-of-sample forecasting power of spread positions, 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–July 2017). Here, I am interested in measuring the incremental forecasting power of spread indicators beyond the well-known predictors. Thus, out-of-sample R^2 is obtained by comparing the model as in Equation (4) to the nested benchmark model with the spread indicator excluded 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 spread indicator; and $\widehat{p}_t$ denotes the recession probability forecast associated with the larger model including the spread indicator. The log loss function used here tends to penalize large prediction errors more heavily than the quadratic loss function. The statistical significance of the larger model against the benchmark model is evaluated using the McCracken (2007) test, which is appropriate for comparing two nested models. The models are recursively estimated at each point in time throughout the out-of-sample evaluation period. I also calculate an average of the coefficients on the spread indicator over the out-of-sample evaluation period in order to see the direction of the effect of the spread indicator on recession probabilities.

Panel A of Table 3 shows the out-of-sample forecasting results, including out-of-sample R^2s, test statistics, and average coefficients ($\overline{\beta}$) on the spread indicator. As is shown in the table, STEEP has incremental forecasting power for recession probabilities beyond term spreads, with an R^2 of 28.6% (3 months ahead) or 22.9% (6 months ahead). STEEP also has incremental forecasting power for recession probabilities beyond bond excess premiums, with an R^2 of 14.8% (3 months ahead) or 6.9% (6 months ahead). Similarly, FLAT has incremental forecasting power beyond term spreads, with an R^2 of 15.4% (3 months ahead) or 11.1% (6 months ahead), and beyond bond excess premiums, with an R^2 of 6.1% (3 months ahead) or 1.7% (6 months ahead). All the results are statistically significant at the 1 or 5% level.

Table 3 also shows the out-of-sample R^2s broken out into recessions and expansions. The performance measure during recessions, denoted by R^2_{Rec}, is always positive for both spread indicators. However, the steepening indicator yields more false detections of recessions during expansionary periods, with a negative value of the performance measure during expansions, denoted by R^2_{Exp}. One reason for such a failure is that speculators maintained steepening positions in the recovery periods immediately following the recessions, as can be seen in Figure 3. For example, even though the 2001 recession came to an end in November, speculators maintained a strong steepening view in the following couple of years or so. Nevertheless, it appears that the benefit of correctly detecting recessions outweighs the cost of falsely detecting recessions given that the spread indicators are statistically significant predictors of future recession probabilities.

Futures trading is a zero-sum game, so it is natural to ask which of the other investor groups took the opposite positions of speculators. To ensure this question, I perform a similar analysis using the spread positions of the other two groups: commercial hedgers and non-reportable players. Although the results are not shown in this paper, I find that, whereas hedgers' spread positions are neutral with no predictive power for recession probabilities, small players' spread positions are predictive of recession probabilities with an incorrect sign. Therefore, small players who are not subject to the reporting requirement appear to have met the demand from informed speculators.

3.2 Forecasting non-farm payroll growth rates

Here, I examine the predictive power of the spread 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 annualized first-release non-farm payroll growth rate between $t+h-1$ and $t+h$ and ε_{t+h} is the forecasting error.[2] As before, z_t includes term spreads, bond excess premiums, and real federal fund rates. A special case with h=0 is referred to as nowcasting.

Panel B of Table 2 shows the in-sample predictive power of the spread indicators for non-farm payroll growth rates. 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 is obtained at the 1% level for every forecasting horizon considered. 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 forecasting horizon. Note that the forecasting power of the spread indicators survives the inclusion of the control variables, suggesting that the spread indicators contain predictive information that is not subsumed by the

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

other business-cycle indicators.

To assess the out-of-sample forecasting power of the spread indicators for non-farm payroll growth rates, I compare the full model as in Equation (6) to the nested benchmark model with the spread indicator excluded. Specifically, the 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 non-farm payroll growth forecast associated with the full and benchmark models, respectively. Here, the first-release non-farm payroll data are used to attain a more real-time testing environment.

Panel B of Table 3 shows the out-of-sample forecasting results for non-farm payroll growth rates. As in recession probability forecasting, STEEP has incremental forecasting power beyond term spreads, with an R^2 of 16.2% (3 months ahead) or 17.2% (6 months ahead), and beyond bond excess premiums, with an R^2 of 10.8% (3 months ahead) or 14.4% (6 months ahead). The test statistic is statistically significant at the 1% level in every case considered. Similarly, FLAT has incremental forecasting power beyond term spreads, with an R^2 of 4.6% (3 months ahead) or 5.1% (6 months ahead), and beyond bond excess premiums, with an R^2 of 2.2% (3 months ahead) or 4.3% (6 months ahead). Although the forecasting improvement of FLAT is smaller than that of STEEP, the results with FLAT are statistically significant at the 1 or 5% level.

Panel B of Table 3 also shows that the forecasting power of the spread 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. Overall, speculators appear to have had a better ability to process payroll information particularly during recessions.

3.3 Spread positions versus outright positions

It is natural to suspect that outright trade in short-term bond futures may be another effective business-cycle strategy because short-term rates are directed by monetary policy decisions. Piazzesi and Swanson (2008) document that speculators' net shares of open interest in Eurodollar futures have predictive power for excess returns on federal funds futures. Furthermore, private information about the business cycle can be revealed through other outright trades in various futures markets because the business-cycle risk is fundamental to all kinds of asset classes and because 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 Treasury and gold futures, which tend to perform well during stressful times. Therefore, I will compare the information content of spread trade in bond futures to that of outright trades in various futures markets.

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 that are associated with the steepening indicator and the outright indicator, respectively. A combination forecast, denoted by $\widehat{p}_{fc,t}$, is defined as a convex combination of the two individual forecasts:

$$\widehat{p}_{fc,t} = \lambda\widehat{p}_{steep,t} + (1 - \lambda)\widehat{p}_{out,t}, \tag{8}$$

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 4 shows the results of the forecast encompassing tests between the spread indicator and the outright indicators 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 does not encompass the information contained in the steepening indicator. These results are valid regardless of the forecasting horizons. 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. Therefore, the steepening indicator appears to have more information about future recession probabilities than the outright indicator in every futures market considered, except for crude oil futures.

I next compare the information content of the steepening indicator to that of the eight outright indicators with respect to non-farm payroll growth forecasting. Let $\widehat{g}_{steep,t}$ and $\widehat{g}_{out,t}$ denote the non-farm payroll growth forecasts that are associated with the steepening indicator and the outright indicator, respectively. Panel B of Table 4 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 does 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. These results hold regardless of the forecasting horizons.

The superior informational content of steepening trade may be explained by the fact that traders view spread trade as a low-risk and low-cost strategy compared to outright trade. Above all, spread trade is largely shielded from any parallel shift in the term structure of interest rates. Particularly, a duration-matched spread trade can be useful when investors are uncertain about near-permanent macroeconomic shocks which might affect yields evenly across all maturities, such as inflation shocks. Such a possibility is not unlikely because forecasting inflation is highly difficult due to model instability (see Stock and Watson 2007). Besides, the slope of the yield curve evolves more smoothly over time, with lower volatility and less tail risk, than the level of the yield curve.

Furthermore, spread trade requires less of a margin than outright trade. For example, at the time of this writing (March 2018), margins are set at 1,600 dollars for ten-year Treasury futures and 3,100 dollars 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 dollars, respectively, but their combined trade would require a margin of only 2,840 dollars.[3] Note that the margin for spread trade is much lower than that for each of the two legs. Ultimately, low margins on spread trade would help informed traders lever their informational advantage.

[3] $6,200 - 0.7 \times 4,800 = 2,840$.

3.4 Evidence of private information

I have found that spread positions contain predictive information about the business cycle, but it does not necessarily mean that speculators have *private* information about the business cycle. It is possible that speculators' slope timing ability is based on some publicly available information that might have some causal effects on the real economy. For example, term spreads and credit spreads may influence the real economy by affecting banks' net interest margins or firms' funding costs. If this is the case, it is unclear whether the predictive power of spread trade is due to private information *per se* or the causal effect of the underlying public information.

The goal of this subsection is to provide evidence that the predictive power of spread positions is in part due to private information held by speculators. To do so, I examine whether the spread indicators can predict non-farm payroll surprises, the differences between the first-release payroll announcements and analysts' forecasts from Action Economics. In the literature, such differences are assumed to be unpredictable to the extent that analysts provide an efficient forecast of the macroeconomic variable. In contrast, if any variable has the predictive power for non-farm payroll surprises, it means that the forecasting variable contains some information that has not been accounted for by professional analysts. That said, I run the following h-month-ahead predictive regression for non-farm payroll surprises:

$$\mathrm{SURP}_{t+h} = \alpha + \beta \mathrm{SPRD}_t + \gamma' z_t + \varepsilon_{t+h}, \tag{9}$$

where SURP_{t+h} denotes the h-month-ahead non-farm payroll surprise. I test for the private information content of the spread indicators by focusing on the coefficient on SPRD_t. The sample period here spans from December 1987 to July 2017, restricted by the availability of analysts' forecast data.

Table 5 shows the in-sample predictive regression results for non-farm payroll surprises. Panel A of the table shows that STEEP can predict payroll surprises two to five months ahead, with statistical significance at the 1% level. The coefficient on STEEP is estimated to be negative, implying that a high level of the steepening indicator is followed by a negative payroll surprise in subsequent months. Panel B of the table shows that FLAT can also predict payroll surprises four to six months ahead, with statistical significance at the 5% level. The coefficient on FLAT is estimated to be positive, implying that a high level of the flattening indicator is followed by a positive payroll surprise in subsequent months. In stark contrast, the other business-cycle indicators, such as term spreads and bond excess premiums, have no predictive power for payroll surprises.

Table 6 shows the out-of-sample forecasting power of the spread indicators for non-farm payroll surprises. Here, the historical-average (or constant) model is selected as a benchmark model and the out-of-sample performance (R^2) is measured using the quadratic loss function. STEEP has the statistically significant forecasting power at the 1% level with an R^2 of 4.6% in three-month-ahead forecasting and at the 10% level with an R^2 of 0.9% in six-month-ahead forecasting. FLAT has the statistically significant forecasting power at the 5% level with an R^2 of 1.2% in three-month-ahead forecasting and at the 1% level with an R^2 of 3.0% in six-month-ahead forecasting. Furthermore, both spread indicators have greater forecasting power during recessions than during expansions in every forecasting horizon considered, with $R^2_{Rec} > R^2_{Exp}$.

Overall, spread indicators are able to predict non-farm payroll surprises a few months before the payroll data releases. This finding suggests that speculators have some information that forecasters have not seen or processed until a few days before the non-farm payroll announcements, and calls into question the traditional assumption that news surprises are unpredictable as forecasters provide an efficient estimate of macroeconomic variables.

4 Spread trade and asset prices

4.1 Information content of spread trade for bond prices

In this subsection, I examine the information content of spread positions for the variation in the term structure of the Treasury yield curve. I also discuss the private nature of the information contained in spread positions by predicting the intraday bond future returns at the times of non-farm payroll data releases.

4.1.1 Forecasting yield changes

Let y_t^T denote the Treasury par yield with a maturity of T at time t. A monthly change in the Treasury yield is then denoted by $\Delta y_t^T = y_t^T - y_{t-1}^T$. Panel A of Table 7 presents the forecasting power of STEEP for the h-month-ahead yield changes, Δy_{t+h}^T. Here, the historical-average (or constant) model is selected as a benchmark model and the out-of-sample performance (R^2) is measured using the quadratic loss function. The table 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. Note that the average coefficients on the steepening indicator are negative for short-term yield changes, implying that a stronger steepening position is followed by a decrease in short-term Treasury yields. This sign is consistent with the previous result that the steepening indicator is associated with a higher probability of recession and a lower non-farm payroll growth rate in subsequent months.

However, the steepening indicator does not have statistically significant power for changes in long-term Treasury yields. To understand this result, I separate the long-term yield changes into two components—the changes in expected interest rates and the changes in term premiums—using the decomposition methods by Kim and Wright (2005) and Adrian, Crump, and Moench (2013). I then test the predictive power of the steepening indicator for each of the two components. The results (not shown in this paper) show that a stronger steepening position is followed by a decrease in expected interest rates but an increase in term premiums, although the statistical significance varies over the decomposition methods and the choices of control variables. That is, the steepening indicator predicts expected interest rates and risk premiums in opposite directions, making the prediction of combined yield changes ambiguous.

Panel B of Table 7 presents the out-of-sample forecasting power of STEEP for monthly yield changes with different maturities 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 5% level for yield changes with two-year maturities. This result suggests that steepening positions have very different predictive information about future interest rates than term spreads, a finding consistent with the very low correlation between STEEP and TMSP (see Table 1).

Panel C of Table 7 presents the out-of-sample forecasting power of STEEP for monthly yield changes with different maturities after EBP is controlled for. Note that 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.

4.1.2 Forecasting slope changes

The slope of the yield curve is associated with the yield spread between long- and short-term bonds. Here, I define a slope change as a monthly change in the 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. Table 8 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 (or constant) model. Note that the average coefficients ($\overline{\beta}$) are positive, meaning that a stronger steepening position is followed by an increase in the slope of the Treasury yield curve (that is, an increase in long-term Treasury yields relative to short-term Treasury yields). The results are statistically significant at the 1% level in one-month-ahead forecasting and at the 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 8 presents the out-of-sample forecasting power of STEEP after TMSP is controlled for. STEEP has incremental forecasting power beyond term spreads, with an out-of-sample R^2 between 4.1 and 6.2% (one month ahead) or between 0.8 and 2.3% (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 to 5% level in three-month-ahead forecasting.

Panel C of Table 8 presents the out-of-sample forecasting power of STEEP 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 3.4 and

4.1%. However, in three-month-ahead forecasting, STEEP substantially loses predictive power after EBP is controlled for.

Overall, steepening positions have predictive information for changes in the slopes of the Treasury yield curve. Specifically, a stronger steepening position is followed by an increase in the slope of the yield curve in the next month. In other words, when speculators take a strong steepening view of the term structure, short-term Treasury bonds tend to outperform than long-term bonds in subsequent months.

4.1.3 Forecasting intraday bond future returns

To discuss the private nature of the information held by speculators, I now examine whether the spread indicators can predict intraday returns on various bond futures over short windows bracketing non-farm payroll data releases. Two short windows are chosen to compute the intraday returns: (i) five minutes before the announcement to five minutes after the announcement and (ii) five minutes before the announcement to 25 minutes after the announcement. The high-frequency future price data come from Thomson Reuters Tick History for the period from January 1996 to July 2017.

Panel A of Table 9 shows the predictive power of the steepening indicator for intraday bond future returns. Here, I use the steepening indicator that is available three months before the non-farm payroll data release. The table shows that the steepening indicator can forecast the intraday response of short-term bond futures to non-farm payroll announcements. Specifically, the steepening indicator is positively associated with the intraday returns on federal funds futures, with a coefficient of 1.32 (ten-minute window) or 1.36 (30-minute window). The steepening indicator is also positively associated with the intraday returns on Eurodollar futures, with a coefficient of 1.77 (ten-minute window) or 1.89 (30-minute window). These results are all statistically significant at the 1% level. The steepening indicator also has some forecasting power for two-year Treasury futures at the 5 or 10% level, depending on the windows. However, the steepening indicator has no predictive power for the intraday returns on long-term Treasury futures.

Panel B of Table 9 shows the predictive power of the flattening indicator for the intraday bond future returns. Again, I use the flattening indicator that is available three months before the non-farm payroll data release. The table shows that the flattening indicator can forecast the intraday response of short-term bond futures to non-farm payroll announcements at the 5% level for federal futures futures, at the 1% level for Eurodollar futures, and at the 10% level for two-year Treasury futures. The flattening indicator has no predictive power for intraday returns on long-term Treasury futures.

An implication of my results is that information held by speculators may have not been fully incorporated into short-term bond future prices until the payroll data release. Such a partial adjustment of prices may be explained by two frictions: imperfect competition and limited capital. If bond futures markets are concentrated in the hands of a finite number of large players, prices may not be fully revealing in the limit as noise traders vanish (see Kyle 1989). In addition, my previous analyses (in Section 3) show that spread positions are particularly informative in recession periods, so the lack of capital may play a role in limiting traders' ability to exploit their private information in difficult times.

To summarize, spread positions contain predictive information about the intraday response of short-term bond futures at the times of subsequent payroll announcements. I interpret this result to imply that speculators have some private information about future payroll data and that such private information is partly incorporated into bond prices at the times of the payroll data releases.

4.2 Information content of spread trade for stock prices

Lucca and Moench (2015) document that about 80% of the S&P 500 excess returns since 1994 had accumulated during the 24-hour windows preceding scheduled FOMC announcements. They also discuss challenges in explaining the pre-FOMC drift with standard asset pricing theory. Given this finding, this subsection examines the information content of the steepening indicator for pre-FOMC stock returns. I also provide evidence that the pre-FOMC drift is due to informed speculation about policy outcomes.

4.2.1 Forecasting pre-FOMC stock drifts

Let r_t^{24h} denote the S&P 500 future return over the pre-FOMC 24-hour window ending at 15 minutes before the FOMC announcement. I then run the predictive regression for the next pre-FOMC stock returns as follows:

$$r_{t+1}^{24h} = \beta_0 + \beta_1 \text{STEEP}_t + \beta_2 \text{VIX}_t + \beta_3 \text{TMSP}_t + \beta_4 \text{EBP}_t + \varepsilon_{t+1}, \tag{10}$$

where r_{t+1}^{24h} refers to the pre-FOMC S&P 500 future return in the next FOMC round and VIX denotes the Chicago Board of Options Exchange (CBOE) VIX index. The sample period here spans from September 1997 to July 2017.

Panel A of Table 10 shows the in-sample predictive regression results. Regression (1) shows that the pre-FOMC 24-hour S&P 500 future returns have an average of 36 basis points in my sample and that the average is statistically significant at the 1% level with a t statistic of 3.11. Regression (2) in the table shows that the steepening indicator has statistically significant power for the next pre-FOMC future return at the 5% level, with a positive coefficient. The positive sign is consistent with my previous result that a stronger steepening position is followed by a decrease in (short-term) interest rates, which may be a good news for stock prices.

Lucca and Moench (2015) find that the pre-FOMC future return is higher in times of high volatility and low term spreads, suggesting that the pre-FOMC stock return varies along the business cycle. Consistent with this finding, Regressions (3)–(5) show that a higher pre-FOMC stock return is preceded by higher volatility, a lower term spread, or a higher excess bond premium.

Importantly, Regression (6) shows that the steepening indicator still has robust predictive power for the next pre-FOMC stock return even after the control variables are included. Furthermore, Regressions (2) and (6) show that, whenever the steepening indicator is included in the regression, the coefficient on the constant term is no longer statistically significant, suggesting that the pre-FOMC drift may be spurious because of an omitted variable. These results suggest the possibility that speculators have a superior ability to forecast policy outcomes and the pre-FOMC drift may be driven by their informed speculation in stock markets right before the scheduled policy announcements.

4.2.2 Additional evidence of informed speculation

I now provide evidence consistent with the argument that the pre-FOMC drift is due to informed speculation about policy outcomes. To do so, I separate the pre-FOMC stock return into two components: same-day return and overnight return. The pre-FOMC same-day return, denoted by r_t^{sd}, is defined as the S&P 500 future return between 9:30 a.m. (Eastern time) on the day of the announcement and 15 minutes before the announcement.[4] The pre-FOMC overnight return, denoted by r_t^{on}, is defined as the difference between the pre-FOMC 24-hour return and the pre-FOMC same-day return. I then run the predictive regression for each component of the pre-FOMC drift as follows:

$$\begin{aligned} r_{t+1}^{sd} &= \beta_0 + \beta_1 \mathrm{STEEP}_t + \beta_2 \mathrm{VIX}_t + \beta_3 \mathrm{TMSP}_t + \beta_4 \mathrm{EBP}_t + \varepsilon_{t+1} \\ r_{t+1}^{on} &= \beta_0 + \beta_1 \mathrm{STEEP}_t + \beta_2 \mathrm{VIX}_t + \beta_3 \mathrm{TMSP}_t + \beta_4 \mathrm{EBP}_t + \varepsilon_{t+1}. \end{aligned} \tag{11}$$

If information is private, investors can be more patient in timing the stock market until the last moment when the information is released. As a result, more private information may be incorporated into asset prices later than less private information. I thus conjecture that the steepening indicator, which I assume to be more private than other business-cycle indicators, is particularly useful for predicting the pre-FOMC same-day returns. In contrast, I expect the VIX and term spreads (which are more readily available) to be significant in predicting the pre-FOMC overnight returns.

Panel B of Table 10 shows the predictive regression results for the pre-FOMC same-day returns. Regression (1) shows that the pre-FOMC same-day returns have an average of 19 basis points and that the average is statistically significant at the 1% level with a t statistic of 3.22. Regression (2) shows that the steepening indicator alone has predictive information about the next pre-FOMC same-day return, with statistical significance at the 1% level. Most importantly, Regression (6) shows that only the steepening indicator and bond excess premiums are important in predicting the pre-FOMC same-day returns at the 1% level. In contrast, the VIX index and term spreads have little predictive power for the pre-FOMC same-day returns.

Panel C of Table 10 shows the predictive regression results for the pre-FOMC overnight returns. Regression (1) shows that the pre-FOMC overnight returns have an average of 17 basis points and that the average is statistically significant at the 5% level with a t statistic of 2.18. Regression

[4] The pre-FOMC same-day return normally captures the return between 9:30 a.m. and 2:00 p.m.

(6) shows that the steepening indicator has no predictive power for the next pre-FOMC overnight returns, whereas the VIX index and term spreads have predictive power at the 1 and 5% levels, respectively.

Overall, the steepening indicator as well as the conventional business-cycle indicators can predict the pre-FOMC stock returns in the subsequent FOMC round. Specifically, the steepening indicator and bond excess premiums have forecasting power for the pre-FOMC same-day returns, whereas the VIX and term spreads have forecasting power for the pre-FOMC overnight returns. Because the steepening indicator is likely to be more private than the VIX index and term spreads, it seems that traders with more private information are willing to wait until the last moment of information release to avoid other risks that have little to do with their information. I thus interpret this result to imply that the specialness of information determines the speed at which information gets incorporated into asset prices.

5 Conclusion

This paper provides new evidence that some investors have private information about business cycles and asset prices. To this end, I focus on the information content of spread trade in bond futures (a purchase of one bond future and a simultaneous sale of another bond future with a different maturity) because the slope of yield curve is closely linked to business and monetary cycles. In addition, spread trade is well suited for informed trading because it is associated with lower risk and lower margin than outright trade.

Using the futures position (COT) data from July 1986 to July 2017, I find that speculators' spread positions have predictive information about subsequent recession probabilities and non-farm payroll growth rates. In addition, spread positions can predict subsequent non-farm payroll surprises, which are the differences between actual payroll announcements and analysts' forecasts. These results suggest that speculators as a group took the correct positions on the slope of the yield curve along phases of the business cycle and that such a slope timing ability is partly due to their private information about non-farm payroll data.

Turning to asset pricing implications of spread positions, I find that speculators' spread positions can predict a significant fraction of the variation in the short end and slope of the Treasury yield curve. More strikingly, spread positions can forecast intraday bond future returns at the times of subsequent payroll announcements. This finding further supports my argument that spread positions contain some private information about non-farm payroll data and that such information is partly incorporated into bond prices at the times of news announcements.

I also find that spread positions have predictive information about subsequent pre-FOMC S&P 500 future returns. If the predictable component associated with spread positions is excluded from the pre-FOMC S&P 500 future returns, the residual component is no longer statistically different from zero, suggesting that the pre-FOMC drift may be a spurious finding. Instead, I argue that speculators engage in informed trading (not necessarily due to leaked information) right before FOMC announcements and that the pre-FOMC stock drift is driven by informed trading about soon-to-be-announced policy outcomes.

Based on my findings, I draw a policy implication. Recent studies find that financial markets react ahead of the FOMC and macroeconomic news releases in a way that is consistent with subsequent news surprises. For example, Bernile, Hu, and Tang (2016) find that the S&P 500 futures' abnormal order imbalances move ahead of the FOMC announcements in a way consistent with following policy surprises. Similarly, Kurov, Sancetta, Strasser, and Wolfe (2017) discover evidence for informed trading that might have occurred right before several macroeconomic news announcements. The authors impute such pre-announcement drifts due to information leakage about news announcements, which implies that policy makers should be more mindful of securing confidential information. However, my result that pre-announcement drifts are predictable a few months ahead suggests that the existence of a pre-announcement drift itself should not be considered sufficient evidence for information leakage.

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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 July 2017.

	STEEP	FLAT	TMSP	EBP	FFR
Panel A: Summary statistics					
Mean	0.40	0.32	1.89	0.05	1.35
Median	0.33	0.17	1.93	-0.07	1.01
Min.	0.00	0.00	-0.49	-1.08	-2.01
Max.	1.00	1.00	3.74	3.05	5.50
Std.	0.38	0.36	1.06	0.58	2.23
Skew.	0.40	0.77	-0.22	1.92	0.06
Kurt.	1.61	2.07	2.07	8.57	1.48
AR(1)	0.92	0.93	0.98	0.91	0.99
Panel B: Correlation matrix					
STEEP	1.00	-0.74	-0.06	0.37	0.05
FLAT		1.00	-0.04	-0.25	-0.06
TMSP			1.00	0.00	-0.62
EBP				1.00	0.03
FFR					1.00

Table 2: **Information content of spreading positions for the business cycle: In-sample evidence**

This table shows the in-sample forecasting power of the spreading indicators for business cycle fluctuations. Panel A reports the h-month-ahead Probit regression results for recession probabilities, and Panel B reports the h-month-ahead linear regression results for the first-release non-farm payroll growth rates. 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 July 2017. 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	1.83***	1.66***	0.77**	FLAT	-1.44**	-1.21**	-0.45
	(4.00)	(3.70)	(2.08)		(-2.48)	(-2.18)	(-0.95)
TMSP	-0.52**	-1.02***	-1.19***	TMSP	-0.59***	-1.10***	-1.27***
	(-2.54)	(-4.07)	(-4.95)		(-3.10)	(-4.42)	(-5.20)
EBP	0.58***	0.56***	0.28**	EBP	0.64***	0.62***	0.32***
	(5.17)	(4.74)	(2.46)		(6.12)	(5.47)	(2.90)
FFR	0.02	-0.08	-0.04	FFR	-0.13	-0.25	-0.13
	(0.10)	(-0.35)	(-0.18)		(-0.70)	(-1.22)	(-0.64)
Const.	-2.04***	-1.22*	-0.45	Const.	-0.43	0.24	0.23
	(-3.22)	(-1.92)	(-0.82)		(-1.07)	(0.56)	(0.55)
adj. R^2	0.45	0.47	0.43	*adj.* R^2	0.39	0.42	0.41
Panel B: Forecasting non-farm payroll growth rates							
STEEP	-1.12***	-1.30***	-1.06***	FLAT	0.73***	0.84***	0.96***
	(-4.83)	(-4.53)	(-3.19)		(3.30)	(3.24)	(3.03)
TMSP	0.18*	0.34***	0.53***	TMSP	0.24**	0.41***	0.59***
	(1.66)	(2.83)	(3.04)		(2.26)	(3.40)	(3.18)
EBP	-0.51***	-0.57***	-0.41**	EBP	-0.58***	-0.65***	-0.47***
	(-3.84)	(-4.96)	(-2.51)		(-4.11)	(-5.13)	(-2.93)
FFR	0.32**	0.37**	0.22	FFR	0.35**	0.39**	0.25
	(2.46)	(2.47)	(1.43)		(2.47)	(2.47)	(1.51)
Lagged	0.56***	0.30***	0.16	Lagged	0.61***	0.37***	0.18
	(4.80)	(2.63)	(1.07)		(4.95)	(3.19)	(1.17)
Const.	0.75***	0.67**	0.37	Const.	-0.08	-0.28	-0.48
	(2.73)	(2.28)	(0.83)		(-0.29)	(-0.85)	(-0.91)
adj. R^2	0.44	0.38	0.23	*adj.* R^2	0.41	0.34	0.22

Table 3: **Information content of spreading positions for the business cycle: Out-of-sample evidence**

This table shows the out-of-sample forecasting power of spread positions for business cycle fluctuations. Panels A and B correspond to the prediction of recession probabilities and the prediction of first-release non-farm payroll growth rates, 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. The sample spans from July 1986 to July 2017. 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–July 2017). 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 spread indicators beyond term spreads and bond excess premiums by comparing the models with and without the spread 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	2.11	28.6	1.79***	41.2	-25.3	1.85	22.9	1.36**	37.0	-32.4
FLAT	-1.73	15.4	2.00***	19.4	-1.4	-1.05	11.1	1.44***	13.5	2.0
After controlling for bond excess premiums										
STEEP	1.51	14.8	1.21**	32.3	-20.7	1.10	6.9	0.91**	21.8	-13.7
FLAT	-0.93	6.1	1.67***	8.7	0.9	-0.44	1.7	0.75**	0.1	3.9
Panel B: Forecasting non-farm payroll growth rates										
After controlling for term spreads										
STEEP	-1.35	16.2	2.17***	25.4	7.9	-1.49	17.2	2.02***	22.2	11.4
FLAT	0.93	4.6	1.66***	6.8	2.6	1.04	5.1	1.59***	7.9	1.9
After controlling for bond excess premiums										
STEEP	-1.10	10.8	2.24***	16.4	7.6	-1.19	14.4	2.65***	17.1	12.1
FLAT	0.65	2.2	0.86**	-0.5	3.8	0.64	4.3	2.00***	2.2	6.0

Table 4: **Forecast encompassing test results between steepening trade and outright trade**

This table shows the results of the Harvey, Leybourne, and Newbold (1998) forecast encompassing test between the steepening indicator and the 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. The sample spans from July 1986 to July 2017. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively.

	3 months ahead			6 months ahead		
		p value			*p* value	
	λ	$H_{\lambda=0}$	$H_{\lambda=1}$	λ	$H_{\lambda=0}$	$H_{\lambda=1}$
Panel A: Forecasting recession probabilities						
Eurodollar	0.82	0.003***	0.223	1.35	0.000***	0.866
Ten-year Treasury	0.86	0.000***	0.254	0.67	0.002***	0.083*
30-year Treasury	1.11	0.000***	0.691	1.03	0.000***	0.553
S&P 500	1.23	0.000***	0.832	1.37	0.000***	0.907
Pound	1.09	0.000***	0.704	1.23	0.000***	0.834
Yen	0.99	0.000***	0.476	1.04	0.000***	0.557
Gold	1.02	0.000***	0.548	1.10	0.000***	0.727
WTI	0.61	0.000***	0.006***	0.65	0.000***	0.041**
Panel B: Forecasting non-farm payroll growth rates						
Eurodollar	0.89	0.000***	0.254	0.86	0.000***	0.146
Ten-year Treasury	1.12	0.000***	0.789	1.05	0.000***	0.658
30-year Treasury	1.07	0.000***	0.687	1.13	0.000***	0.796
S&P 500	1.25	0.000***	0.946	1.36	0.000***	0.987
Pound	0.98	0.000***	0.443	1.20	0.000***	0.890
Yen	1.18	0.000***	0.865	1.21	0.000***	0.882
Gold	1.08	0.000***	0.725	1.11	0.000***	0.820
WTI	0.93	0.000***	0.304	1.02	0.000***	0.555

Table 5: **Predictive power of spread positions for non-farm payroll surprises: In-sample evidence**

This table shows the h-month-ahead predictive regression results for non-farm payroll surprises, which are the differences between actual non-farm payroll announcements and analysts' forecasts from Action Economics. The sample period here spans from December 1987 to July 2017, restricted by the availability of analysts' forecast data. Panels A and B show the predictive power of the steepening and flattening indicators, respectively, for various forecasting horizons. 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.

Month (h)	h=1	h=2	h=3	h=4	h=5	h=6
Panel A: The predictive power of the steepening indicator						
STEEP	-0.21*	-0.30***	-0.40***	-0.38***	-0.32***	-0.14
	(-1.69)	(-2.65)	(-3.39)	(-3.38)	(-2.68)	(-1.06)
TMSP	0.01	0.02	-0.01	-0.00	0.04	0.05
	(0.15)	(0.28)	(-0.22)	(-0.06)	(0.59)	(0.85)
EBP	-0.08	-0.04	-0.01	-0.04	-0.03	-0.05
	(-1.30)	(-0.76)	(-0.14)	(-0.69)	(-0.48)	(-0.88)
FFR	-0.00	0.00	-0.03	-0.03	-0.00	-0.01
	(-0.04)	(0.02)	(-0.46)	(-0.47)	(-0.03)	(-0.10)
Const.	0.07	0.09	0.19	0.17	0.06	-0.04
	(0.58)	(0.68)	(1.61)	(1.34)	(0.42)	(-0.29)
adj. R^2	0.01	0.01	0.02	0.02	0.01	0.00
Panel B: The predictive power of the flattening indicator						
FLAT	0.13	0.13	0.22*	0.26**	0.30**	0.29**
	(0.92)	(1.01)	(1.79)	(2.29)	(2.47)	(2.57)
TMSP	0.02	0.03	0.01	0.02	0.06	0.07
	(0.31)	(0.45)	(0.09)	(0.26)	(0.87)	(1.04)
EBP	-0.10	-0.08	-0.05	-0.07	-0.05	-0.05
	(-1.64)	(-1.34)	(-0.87)	(-1.23)	(-0.81)	(-0.85)
FFR	0.00	0.01	-0.02	-0.02	0.01	0.00
	(0.02)	(0.07)	(-0.34)	(-0.32)	(0.13)	(0.07)
Const.	-0.07	-0.09	-0.07	-0.10	-0.20	-0.22
	(-0.47)	(-0.60)	(-0.51)	(-0.74)	(-1.33)	(-1.44)
adj. R^2	0.00	-0.00	0.00	0.01	0.01	0.01

Table 6: **Predictive power of spread positions for non-farm payroll surprises: Out-of-sample evidence**

This table shows the out-of-sample forecasting power of spread positions for non-farm payroll surprises, differences between actual non-farm payroll announcements and analysts' forecasts from Action Economics. 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. The sample period here spans from December 1987 to July 2017, restricted by the availability of analysts' forecast data. Here, I divide the entire sample period into two subperiods: the first in-sample estimation period (December 1987–December 1999) and the out-of-sample evaluation period (January 2000–July 2017). 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 spread indicators relative to the historical-average (or constant) benchmark model. The out-of-sample R^2 is measured using the quadratic loss function, and 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}
STEEP	-0.46	4.6	1.50***	14.7	2.4	-0.22	0.9	0.59*	4.6	0.1
FLAT	0.31	1.2	0.96**	5.8	0.2	0.39	3.0	1.98***	5.1	2.5

Table 7: **Forecasting power of the steepening indicator for yield changes**

This table presents the out-of-sample forecasting power of the steepening indicator for monthly changes in Treasury yields with different maturities. 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 July 2017. 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–July 2017). 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 the 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: Against the historical-average model										
3-month Treasury	-0.14	9.6	1.80***	11.0	3.8	-0.13	8.2	1.57***	10.0	0.6
6-month Treasury	-0.11	8.5	1.89***	7.4	13.5	-0.14	9.9	1.58***	9.8	10.2
1-year Treasury	-0.09	5.8	1.66***	4.8	8.3	-0.15	9.4	1.51***	8.7	11.1
2-year Treasury	-0.06	1.7	0.90**	1.1	2.8	-0.15	5.7	1.25**	4.5	8.0
5-year Treasury	-0.00	-1.0	-1.86	-0.9	-1.5	-0.11	1.4	0.57*	1.0	2.2
10-year Treasury	0.03	-1.2	-2.25	-0.7	-2.6	-0.07	0.1	0.09	-0.2	0.9
20-year Treasury	0.03	-1.0	-1.43	-0.3	-2.9	-0.05	-0.2	-0.17	-0.6	0.8
Panel B: Against the model including term spreads										
3-month Treasury	-0.13	9.3	1.95***	10.6	4.0	-0.13	8.1	1.78***	9.7	1.6
6-month Treasury	-0.10	8.1	1.94***	7.1	12.7	-0.14	9.8	1.75***	9.6	10.8
1-year Treasury	-0.08	5.4	1.67***	4.7	7.2	-0.15	9.2	1.61***	8.5	11.1
2-year Treasury	-0.05	1.5	0.87**	1.2	2.2	-0.14	5.5	1.26**	4.4	7.9
5-year Treasury	-0.00	-1.0	-1.83	-0.8	-1.6	-0.11	1.5	0.58*	1.0	2.4
10-year Treasury	0.03	-1.3	-2.34	-0.7	-2.6	-0.07	0.2	0.17	-0.1	1.1
20-year Treasury	0.03	-1.1	-1.58	-0.4	-2.8	-0.05	-0.1	-0.09	-0.5	1.0
Panel C: Against the model including bond excess premiums										
3-month Treasury	-0.09	4.4	1.59***	4.8	2.6	-0.09	4.9	1.51***	5.6	2.0
6-month Treasury	-0.05	2.7	1.27**	1.6	6.6	-0.10	5.6	1.39***	5.0	8.0
1-year Treasury	-0.03	1.1	0.79**	0.4	2.7	-0.12	5.4	1.25**	4.2	8.2
2-year Treasury	-0.00	-0.4	-0.58	-0.4	-0.3	-0.13	3.6	1.06**	2.2	6.1
5-year Treasury	0.03	-1.0	-1.80	-0.5	-2.0	-0.11	0.9	0.41*	0.1	2.7
10-year Treasury	0.05	-0.4	-0.57	0.7	-3.0	-0.08	-0.1	-0.06	-0.9	2.0
20-year Treasury	0.05	-0.3	-0.40	1.0	-3.5	-0.06	-0.2	-0.13	-1.0	2.0

Table 8: **Forecasting power of the steepening indicator for slope changes**

This table presents the out-of-sample forecasting power of the steepening indicator for monthly changes in the slope of the Treasury yield curve. 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 July 2017. 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–July 2017). 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 the 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: Against the historical-average model										
10-year Treasury	0.16	4.4	1.70***	8.8	2.3	0.06	0.9	0.75**	2.1	0.4
15-year Treasury	0.17	5.0	1.80***	9.2	2.8	0.08	1.6	1.06**	3.4	0.6
20-year Treasury	0.17	5.5	1.86***	10.0	3.1	0.08	2.0	1.16**	4.1	0.8
25-year Treasury	0.17	6.0	1.92***	10.8	3.6	0.09	2.2	1.25**	4.4	1.1
Panel B: Against the model including term spreads										
10-year Treasury	0.16	4.1	2.00***	8.1	2.2	0.05	0.8	0.74**	1.7	0.3
15-year Treasury	0.16	4.7	2.13***	8.6	2.6	0.07	1.4	1.11**	3.0	0.6
20-year Treasury	0.16	5.2	2.19***	9.3	3.0	0.08	1.8	1.21**	3.6	0.8
25-year Treasury	0.17	5.7	2.28***	10.2	3.4	0.08	2.0	1.30**	3.9	1.1
Panel C: Against the model including bond excess premiums										
10-year Treasury	0.14	3.4	1.87***	5.0	2.6	0.01	-0.2	-0.35	-0.4	-0.1
15-year Treasury	0.13	3.5	1.86***	4.7	2.8	0.03	0.2	0.28	0.2	0.2
20-year Treasury	0.13	3.6	1.84***	4.5	3.0	0.03	0.3	0.39*	0.2	0.4
25-year Treasury	0.13	3.8	1.85***	4.5	3.4	0.03	0.3	0.38*	0.1	0.5

Table 9: **Predicting intraday bond future returns at the times of non-farm payroll announcements**

This table shows the results of predicting the intraday bond future returns at the times of non-farm payroll announcements using the futures position data that are available three months before the payroll announcements. Panels A and B show the predictive ability of the steepening and flattening indicators, respectively. The intraday bond future returns are computed over the two brief windows: (i) five minutes before the announcement to five minutes after the announcement and (ii) five minutes before the announcement to 25 minutes after the announcement. 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.

	$[t-5\ min, t+5\ min]$			$[t-5\ min, t+25\ min]$		
	β	t stat.	$adj.\ R^2$	β	t stat.	$adj.\ R^2$
Panel A: The forecasting power of the steepening indicator						
Federal funds	1.32***	2.99	3.1	1.36***	3.15	2.8
Eurodollar	1.77***	3.11	2.5	1.89***	3.32	2.8
Two-year Treasury	3.05**	2.04	0.5	2.95*	1.81	0.5
Five-year Treasury	6.51	1.60	0.3	4.56	1.16	-0.1
Ten-year Treasury	8.92	1.58	0.3	5.54	1.02	-0.1
30-year Treasury	11.77	1.49	0.3	6.40	0.84	-0.2
Panel B: The forecasting power of the flattening indicator						
Federal funds	-0.99**	-2.53	1.4	-0.93**	-2.50	1.0
Eurodollar	-1.41***	-2.77	1.3	-1.53***	-3.14	1.5
Two-year Treasury	-2.57*	-1.79	0.2	-2.32*	-1.73	0.1
Five-year Treasury	-6.04	-1.65	0.2	-5.31	-1.51	0.0
Ten-year Treasury	-7.46	-1.46	0.1	-5.68	-1.16	-0.1
30-year Treasury	-6.69	-0.98	-0.2	-3.10	-0.43	-0.4

Table 10: **Predicting pre-FOMC S&P 500 future returns**

This table shows the in-sample regression results for predicting the next pre-FOMC S&P 500 future returns. Panel A shows the results for predicting the pre-FOMC 24-hour returns; Panel B shows the results for predicting the pre-FOMC same-day returns; and Panel C shows the results for predicting the pre-FOMC overnight returns. The sample period here spans from September 1997 to July 2017, restricted by the availability of the intraday S&P 500 futures data from Thomson Reuters 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 (CBOE) 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 24-hour returns						
Reg. (1)	0.36***					0.0
	(3.11)					
Reg. (2)	0.06	0.67**				5.3
	(0.64)	(2.39)				
Reg. (3)	-0.45**		3.95***			7.9
	(-2.19)		(3.19)			
Reg. (4)	0.69***			-0.18**		2.3
	(5.30)			(-2.11)		
Reg. (5)	0.33***				0.51***	8.8
	(3.68)				(2.87)	
Reg. (6)	0.06	0.34**	2.63***	-0.22***	0.23	14.2
	(0.35)	(2.05)	(2.82)	(-3.30)	(1.49)	
Panel B: Forecasting the pre-FOMC same-day returns						
Reg. (1)	0.19***					0.0
	(3.22)					
Reg. (2)	-0.01	0.44***				12.7
	(-0.14)	(3.72)				
Reg. (3)	-0.16		1.68***			7.6
	(-1.60)		(3.48)			
Reg. (4)	0.27***			-0.04		0.3
	(3.09)			(-0.99)		
Reg. (5)	0.17***				0.30***	16.6
	(3.90)				(5.10)	
Reg. (6)	0.14	0.28***	0.08	-0.05*	0.23***	21.0
	(1.32)	(2.69)	(0.12)	(-1.70)	(3.08)	
Panel C: Forecasting the pre-FOMC overnight returns						
Reg. (1)	0.17**					0.0
	(2.18)					
Reg. (2)	0.06	0.24				0.2
	(1.12)	(1.11)				
Reg. (3)	-0.30*		2.26**			2.8
	(-1.69)		(2.28)			
Reg. (4)	0.42***			-0.13**		1.4
	(4.79)			(-2.04)		
Reg. (5)	0.16**				0.21	1.3
	(2.31)				(1.44)	
Reg. (6)	-0.08	0.06	2.55***	-0.17**	-0.00	4.1
	(-0.44)	(0.43)	(2.67)	(-2.55)	(-0.03)	

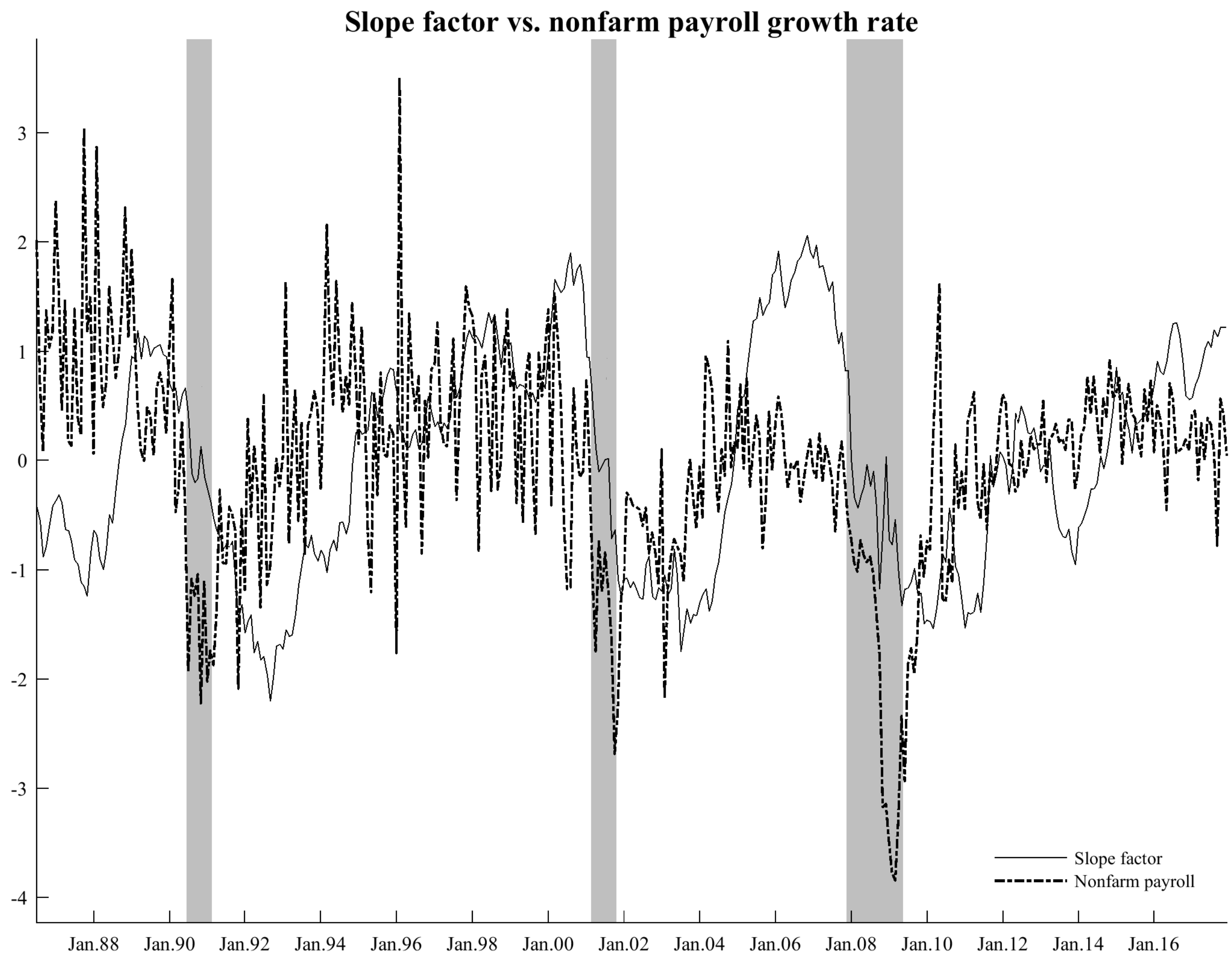

Figure 1: Time series of the slope of the yield curve and the non-farm payroll growth rate.
The slope factor (solid line) is the second principal component of a cross-section of Treasury yields with maturities from 1 to 30 years, and the first-release vintage data on non-farm payroll growth rates (dotted line) are available from the Federal Reserve Bank of Philadelphia. The shaded areas refer to the three NBER-designated recessions included in my sample period.

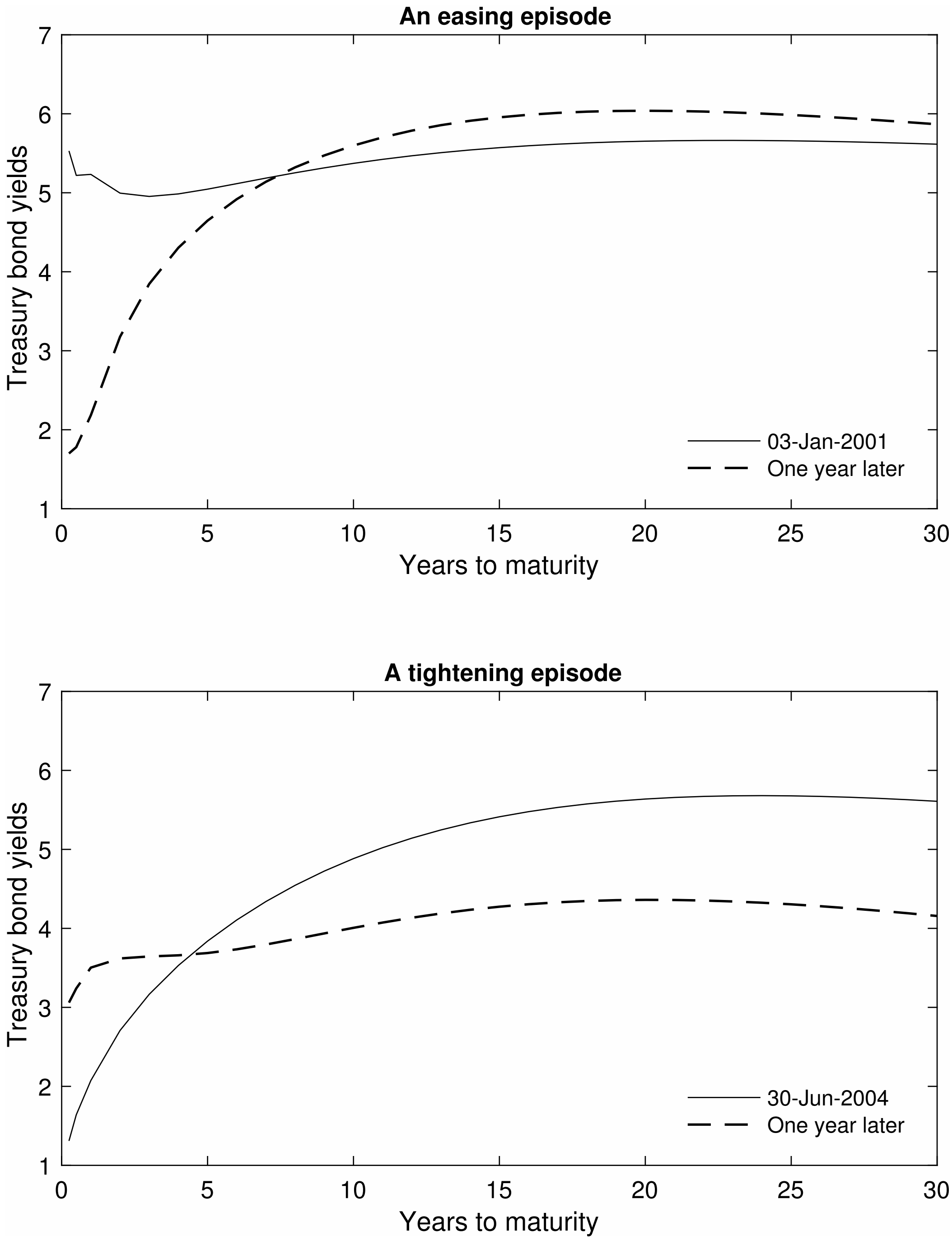

Figure 2: The evolution of the term structure during two episodes of the monetary cycle.
Panel A compares the term structure of Treasury yields on January 3, 2001 (the starting date of a monetary easing) to the term structure one year later. Panel B compares the term structure of Treasury yields on June 30, 2004 (the starting date of a monetary tightening) to the term structure one year later.

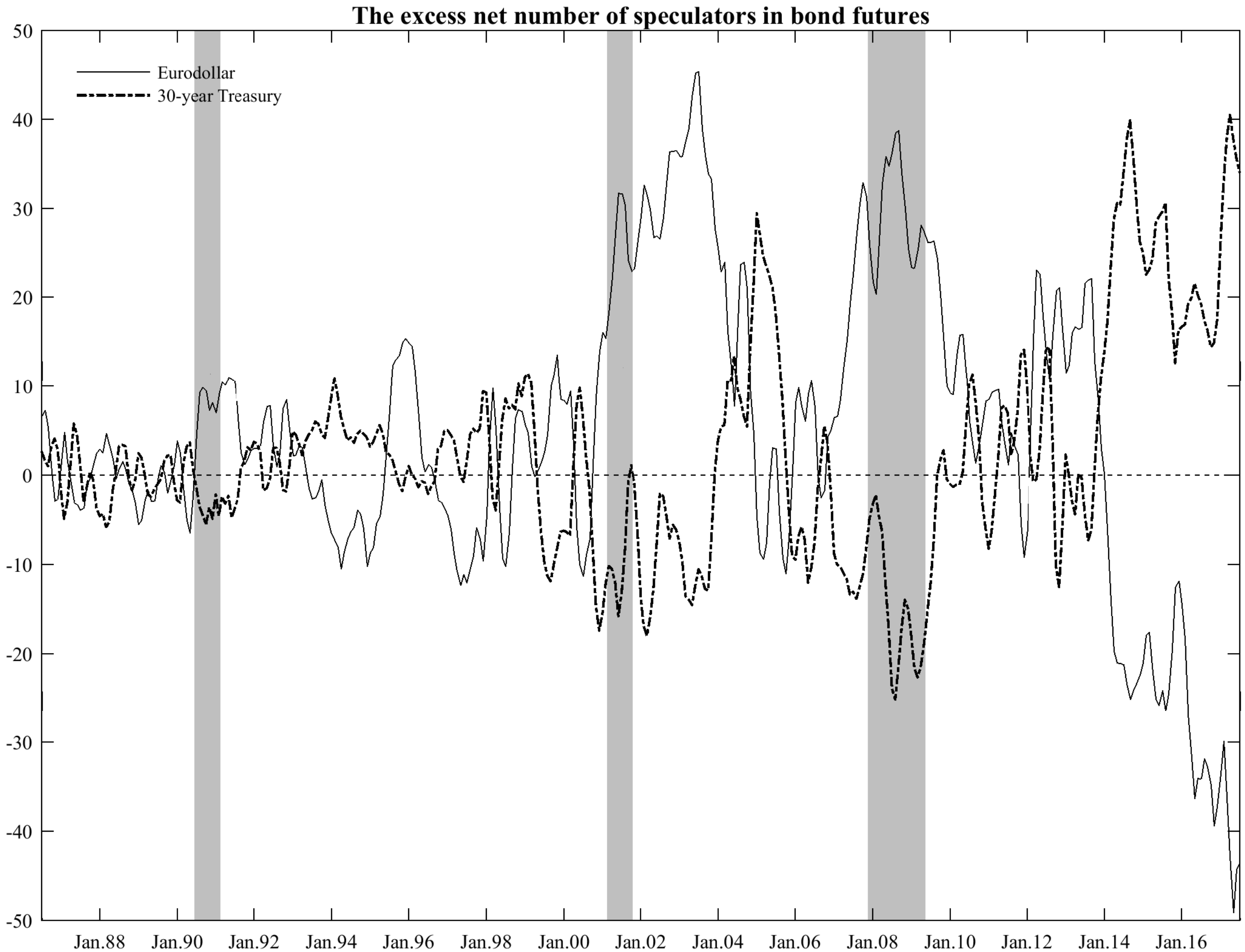

Figure 3: Time series of the excess net number of speculators in bond futures
The solid and dotted lines correspond to Eurodollar futures and 30-year Treasury futures, respectively. The shaded areas refer to the three NBER-designated recessions included in my sample period.

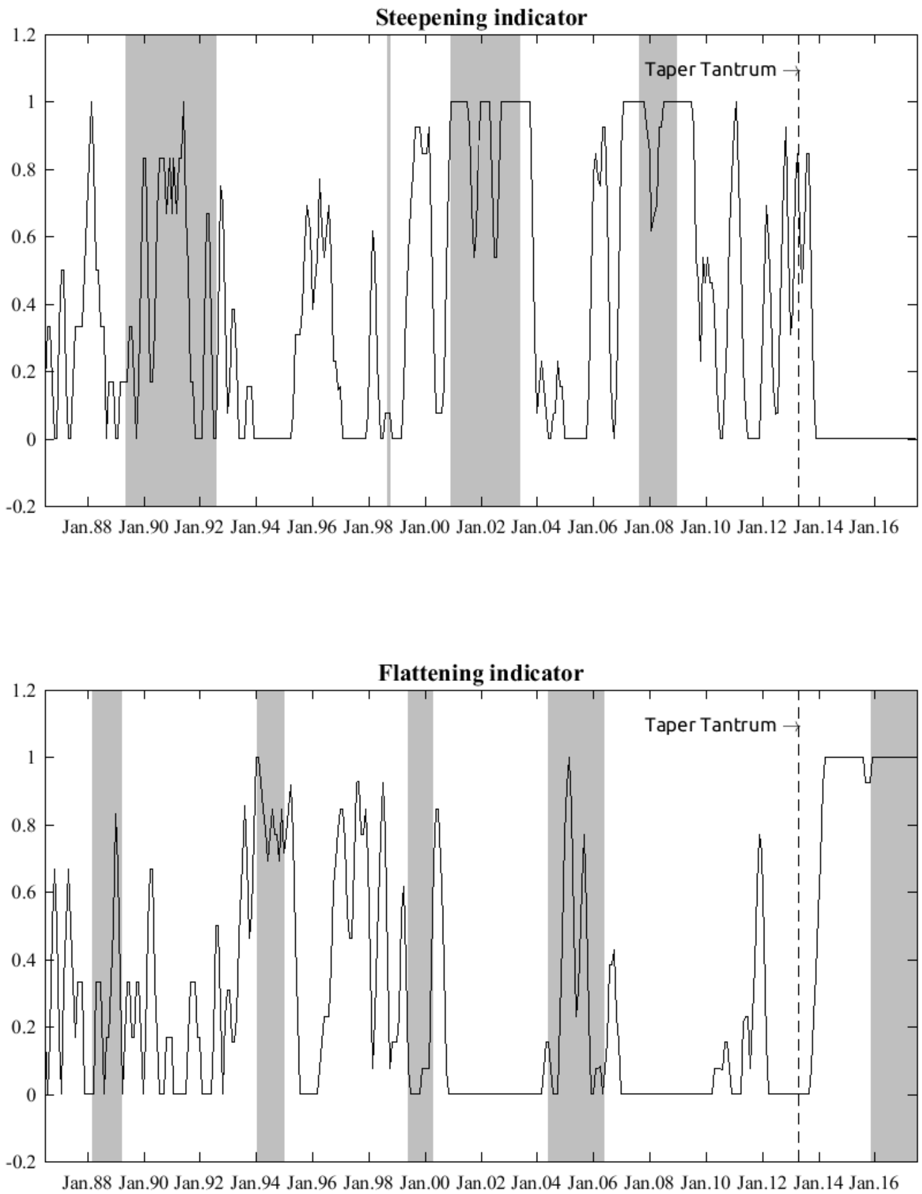

Figure 4: Time series of the spread indicators
Panel A shows the time series of the steepening indicator, with the shaded areas referring to the four easing episodes included in my sample: (i) June 6, 1989–September 4, 1992; (ii) September 29, 1998–November 17, 1998; (iii) January 3, 2001–June 25, 2003; and (iv) September 18, 2007–January 28, 2009. 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–May 4, 1989; (ii) February 4, 1994–February 1, 1995; (iii) June 30, 1999–May 16, 2000; (iv) June 30, 2004–June 29, 2006; and (v) December 17, 2015–the end of the sample period. 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.