# Risk Premia in the 8:30 Economy

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Abstract: Financial asset returns are widely agreed to be somewhat predictable. This paper is concerned with decomposing these predictable returns into those earned in short windows around the times of macroeconomic news announcements (which mostly come out at 8:30am) and the predictable returns that are earned at other times. The statistically significant predictability in bond returns appears to accrue only around news announcements–were it not for the effects of news announcements, we could not reject the expectations hypothesis. This can be interpreted as direct evidence for a time-varying price of jump risk. It also motivates consideration of a trading strategy that takes a position in bonds only around news announcements.

## 1. Introduction

Asset returns are widely believed to be at least somewhat predictable. Today's term structure of interest rates is useful for forecasting future bond returns, contradicting the expectations hypothesis of the term structure. Somewhat more controversially, financial ratios such as the dividend yield seem to forecast future stock returns.

In this paper, we take the measured predictability of monthly returns as given and examine when during the month the predictable return accrues. This might seem to be a peculiar question were it not for the fact that U.S. macroeconomic news announcements arrive at deterministic times during the month. Because many important announcements are made at 8:30am Eastern time, we refer collectively to the small time windows around important macro announcements as the 8:30 economy. Thus, the question is asked in this paper is: do standard predictors forecast returns in the 8:30 economy, at other times, or both?

Our basic strategy is straightforward. We decompose returns into the sum of those accruing in 15 minutes windows around major news announcements and those accruing at other times. We first replicate the standard predictive regressions for total returns and then run the regressions separately for the two additive components.

The main result is that for bond returns, nearly all of the standard evidence for predictability seems to come from predictability in the 8:30 economy. We find little evidence that bond returns outside of announcement windows are forecastable. Econometrically, the basis for our finding is that the predictive regressions are much more precisely estimated for announcement-window returns. Things are quite different for equity returns–for these most of the predictability comes outside the announcement windows.

There are a number of potentially important implications of the bond return results. The returns earned around news announcements can be thought of as jumps in price with random magnitude but deterministic timing. The returns outside the announcement window include price movements that are small enough that they can usefully be thought of as following a continuous diffusion and also include any jumps in response to discrete lumps of news arriving outside the announcement windows. Under standard assumptions, the predictability of announcement-window returns implies that jump risk in the 8:30 economy is priced, and indeed pays a time-varying risk premium. This calls into question the practice (in some academic work, on Wall Street, and in policymaking institutions) of interpreting market jumps in response to macro news simply in terms of changes in expectations. Further, because the news arriving in the 8:30 economy is macro news, these results potentially shed new light on the pricing of macro risk. While the main point of the paper is simply to document the empirical regularities, we briefly explore some of these implications.

The plan for the remainder of this paper is as follows. Section 2 describes the data and the predictive regressions. Section 3 presents pseudo-out-of-sample results for general predictability and Sharpe ratios for investment strategies. Section 4 discusses the economic interpretation and implications of these results. Section 5 concludes.

## 2. Predictability decomposition

This paper considers predictive regressions of the form

$$r_{t,t+h} = \alpha + \beta' x_t + \varepsilon_{t,t+h} \tag{1}$$

where $r_{t,t+h}$ is a continuously compounded asset return from the end of month $t$ to the end of month $t+h$ and $x_t$ is a vector of predictors at the end of month $t$. The return can be decomposed into two components: (A)–the cumulative returns earned from 5 minutes before to 10 minutes after major macro announcements and (NA)–cumulative returns at all other times. Calling these components $r^{A}_{t,t+h}$ and $r^{NA}_{t,t+H}$, respectively, we have, $r_{t,t+h} = r^{A}_{t,t+h} + r^{NA}_{t,t+h}$. We consider predictive regressions for the two components separately:

$$r^{A}_{t,t+h} = \alpha_A + \beta'_A x_t + \varepsilon^{A}_{t,t+h} \tag{2}$$

and

$$r_{t,t+h}^{NA} = \alpha_{NA} + \beta'_{NA} x_t + \varepsilon_{t,t+h}^{NA} \tag{3}$$

We are interested in whether the statistically significant predictive power found in (1) stems from either or both of the two components. Since the explanatory variables are identical, the coefficients in (2) and (3) sum to those in (1) ($\beta = \beta_A + \beta_{NA}$). The same is true for the OLS estimates of these parameters. Statistical significance, however, is another matter. For example, take the simple case that the two component regressions both have the same $x$ variables and parameter values ($\beta_A = \beta_{NA}$), the same residual variance, and zero residual covariance. In this case, the ordinary $t$ statistic in (1) will be larger than that in (2) or (3) by a factor of $\sqrt{2}$.[1] However, the slope coefficients and error variances are surely different in announcement and non-announcement windows. Accordingly, it is possible that the slope coefficients in (2) or (3) could be more or less significant than in (1).

*2.1 The Data*

The asset returns that we use are returns on five-, ten- and thirty-year bond futures and S&P stock futures, trading on the Chicago Mercantile Exchange (CME). The sample period for the bond futures is from November 1988 to December 2007, while the sample period for the stock futures is from February 1993 to December 2007. The data are from Tickdata and the CME[2]. In each case we take returns on the front contract in

[1] The overall $\beta$ is twice the component $\beta$, and the only other part of the $t$-statistics that differs in the overall is the measure of the residual standard error, which will be related by

$$std(\hat{\varepsilon}_{t,t+h}) = \sqrt{std(\hat{\varepsilon}_{t,t+h}^{A})^2 + std(\hat{\varepsilon}_{t,t+h}^{NA})^2} = \sqrt{2} std(\hat{\varepsilon}_{t,t+h}^{A})$$

[2] All macroeconomic announcements come out within the regular trading hours for bond futures, but most macroeconomic annoucements come out at 8:30am Eastern Time, which is before floor trading begins in stock futures. There is however trading in stock futures at 8:30am on the Globex electronic trading platform. Tickdata includes Globex quotes since July 2003; we supplement this data with Globex stock futures quotes from the CME for the earlier period.

the quarterly cycle, rolling into a new contract on the first day when its trading volume exceeds that of the old front contract. In forecasting asset returns, one normally uses excess returns over a measure of the risk-free rate. However, here we are working with futures quotes. Apart from the margin requirement, no upfront money is required to enter into a futures contract. For this reason, we simply use the raw futures returns as the left-hand-side variable.[3]

For bond futures returns, the predictors that we use are the first three or five principal components of the zero-coupon unsmoothed Fama-Bliss yields from CRSP (Cochrane and Piazzesi (2005, 2008)). The first three principal components have interpretations as level, slope and curvature, respectively and jointly account for the vast majority of the cross-sectional variation in yields. However, some authors (Cochrane and Piazzesi (2008) and Duffee (2008)) argue that the fourth and fifth principal components may nonetheless be useful for predicting excess returns, and so we consider these as well.

For stock futures returns, the predictors are the log dividend yield and the variance risk premium, following Bollerslev, Tauchen and Zhou (2009). The log dividend yield is the ratio of the twelve month moving average of dividends to stock prices, as backed out from the comparison of CRSP value-weighted stock returns inclusive and exclusive of distributions. The variance risk premium is the difference between options-implied volatility and realized volatility. There is some evidence of instability over time in which, if any, variables have predictive power for stock returns (e.g. Welch and Goyal (2008)). But Bollerslev, Tauchen and Zhou provide evidence that these two variables have the strongest predictive power for stock returns over the 1990s and 2000s, which is our sample

[3] Another way of saying this is that spot-futures arbitrage means that the futures price must be the spot price adjusted for the cumulative risk-free interest rate until the futures expiration. So, our raw futures returns should be exactly the same as excess bond returns over the riskfree rate, to the extent that spot-futures arbitrage applies. Running the regression using twelve-month-horizon five-year futures returns gives very similar results to what one gets over the same sample period using the excess return on four- or five-year Fama Bliss zero-coupon bonds over the one-year yield, as considered by Cochrane and Piazzesi (2005, 2008).

period.

Finally, our announcement window runs from 5 minutes before to 10 minutes after 10 major macroeconomic announcements: nonfarm payrolls/unemployment, CPI, PPI, trade balance, retail sales, personal income,durable goods, initial unemployment claims, industrial production and scheduled FOMC announcements.

*2.2 Results*

Table 1 shows the results from estimating the three regressions for these four different assets at horizons $h = 1$ and $h = 6$ months. We report the OLS coefficient estimates along with p-values for a test of the joint significance of all slope coefficients, the regression R-squared, and a p-value for testing the hypothesis that $\beta_A = \beta_{NA}$.

For bond returns, the estimates of the announcement-window coefficients, $\beta_A$, are consistently smaller than the estimates for the full return, $\beta$. But the announcement-window $\beta$s are much more precisely estimated. As a result, the hypothesis that $\beta_A = 0$ can be rejected in all cases. The non-announcement window $\beta$s are imprecisely estimated and are not statistically significantly different from zero at conventional significance levels. At the one-month horizon ($h = 1$), the hypothesis that $\beta_{NA} = 0$ cannot be rejected at the 5 percent level, with p-values ranging from 7 to 15 percent. So there is strong evidence against the expectations hypothesis of the term structure, but only in small windows around news announcements.

Of course, given that $\beta^A$ is small relative to the total $\beta$ and that the component $\beta$s sum to the total one, it must be that $\beta^{NA}$ has a relatively large point estimate. Statistical significance fails because of the imprecision with which $\beta^{NA}$ is estimated. Indeed, the hypothesis that $\beta_A = \beta_{NA}$ is not rejected in any case. We return to this point below.

As is common in this field, at the longer horizon ($h = 6$ ), the measured evidence of predictability is stronger, likely partly reflecting the econometric issues associated with longer-horizon predictive regressions, in which both left- and right-hand-side variables are quite persistent, creating something akin to a spurious regression. Nevertheless, even at this longer horizon, the slope coefficients in estimating equation (3) for bond returns are only borderline significant, whereas their counterparts in the announcement-window regression (equation (2)) are highly significant. And the R-squared values are about twice as high in the announcement window regression as in the non-announcement-window regression.

The results are quite different for stock futures returns. As in the case of bond returns, the standard errors in the estimation of equation (2) are much smaller than those in (3). But for stock returns the estimates of $\beta_A$ are tiny. As a result, we cannot reject the hypothesis that $\beta_A = 0$, even though we can reject the null that $\beta_{NA} = 0$. All of the significant predictability in bond returns is in announcement windows; for stocks it seems to be the opposite.

Table 2 provides a different metric for comparing the predictability of returns overall and in announcement windows. This table first shows the fraction of the variance of returns that occurs in announcement windows: $\frac{Var(r^A_{t,t+1})}{Var(r_{t,t+1})}$ for the different futures returns. Consistent with prior research (e.g. Andersen, Bollerslev, Diebold and Vega (2007)) this is a bit above 10 percent for bond returns, and a good bit smaller for stock returns. The table then shows the fraction of the variance of *expected* returns that occurs in announcement windows: $\frac{Var(\hat{\beta}_A^{'} x_t)}{Var(\hat{\beta}^{'} x_t)}$. For bond returns, this is a good bit higher (over 20 percent), although it is negligible for stock returns. For the thirty-year bond, 11 percent of returns accrue at the time of news announcements, but 26 percent of expected returns comes at these times.[4]

[4]It is quite common to regress jumps in asset prices in short windows around news announcements on the unexpected components of those announcements (e.g. Anderson, Bollerslev, Diebold and Vega (2007), Faust, Rogers, Wang and Wright (2005)). The conventional interpretation of such a regression is as measuring the effect of a surprise on asset returns. The result in this paper indicates that for bond returns, part of the jump around news announcements is expected, and not the response to news. However, the fraction of the variance in announcement-window returns that is expected, $\frac{Var(\hat{\beta}_A^{'} x_t)}{Var(r^A_{t,t+1})}$ is very small, and so it seems reasonable to neglect this effect.

Figure 1 plots the time series of expected announcement-window returns, $\hat{\beta}_A' x_t$ for all four asset returns considered in this paper. This risk premium is lowest around business cycle peaks and at times of financial market stress, such as the fall of 1998. It is highest around business cycle troughs and in the early stages of expansions. The patterns for are similar for the three different bond futures, but the volatility of the risk premia is greatest for the longest duration futures, which is to be expected.

*2.3 Further Decomposition of Announcement-Window Bond Risk Premia*

Given that the significant risk premia in the bond market seems to be earned around times of macroeconomic news announcements, one might wonder which announcements are associated with predictable returns. One could regress returns in the same 15 minute window around each announcement separately on the predictors, $x_t$. We do this in Table 3, for predicting ten-year futures returns using the first three principal components alone. At the one-month horizon, the returns around retail sales, initial claims and PPI announcements are significantly predictable, at the five percent level. At the six-month horizon, the returns around GDP and industrial production announcements are also significantly predictable. This might suggest that the pricing of jump risk is especially important around these announcements. However, the confidence intervals are quite wide. This is not surprising because as one breaks returns into smaller increments, if these increments are alike, one would expect the coefficients in predictive regressions to go to zero faster than their standard errors. We would interpret the results on exactly which announcement-window returns are predictable with caution. Note that because different announcements can come out concurrently, the coefficient estimates in Table 3 added up across all announcements do not exactly sum to $\beta_A$.

## 3. Pseudo-out-of-sample predictability and Sharpe ratios

In this section, we consider questions about pseudo-out-of sample predictive power for bond futures returns.

*3.1 Out-of-sample mean-square errors*

We first evaluate one-month-ahaed out-of-sample forecasts of returns from equations (1), (2) and (3). The forecasts are constructed recursively, with the first forecast made for January 1995, using data only through December 1994, and the sample period is then rolled forward one month at a time for a total of 13 years of out-of-sample observations. Table 4 shows the mean-square errors of the forecasts based on these three equations relative to the mean square errors imposing that the slope coefficients are equal to zero (estimating the intercept alone). These are nested forecast comparisons in which the "large" model has $k+1$ parameters, where $k$ is the number of elements in $x_t$, and the "small" model has just one parameter.

For the non-announcement-window and combined regressions, the entries in Table 4 are all greater than 1. Note that this is a shorter sample than is typically used for predictive regressions in finance, which may account for the out-of-sample predictive performance for the combined regression being weaker than is typically found in this literature. However, despite the rather short sample period, for the announcement-window regression (equation (2)), the entries in Table 4 are all less than 1, meaning that the inclusion of the predictors lowers mean-square forecasting error. The table also reports the p-values from the Diebold-Mariano test for equality of mean square error (Diebold and Mariano (1995)) with and without the predictors $x_t$ , using the asymptotic critical values of Clark and McCracken (2005), appropriate for this nested forecast comparison. The reduction in mean-square error for the announcement-window regresion is statistically significant for the ten- and thirty-year bond futures returns, and is close to significant for the five-year returns.

*3.2 Trading strategies*

We also explore the profitability of four strategies intended to exploit the predictability of bond returns found here. While details are below, the first three strategies exploit in a natural way the following three approaches: (i) invest for the full month based on the regression on the full monthly return, (ii) take a position only during the announcement window based on the announcement window regression, and (iii) take a position only outside the announcement window base on the non-announcement window regression. Finally, strategy (iv) invests for the entire month as in (i), but bases the strategy on the announcement window regression. This "hybrid" strategy could be motivated by the belief that $\beta^A$ is the best estimate of predictability for the full month because $\beta_{NA}$ is so poorly measured.[5] The precise definitions of the strategies are:

(i) At the end of month $t$, regression (1) is run to obtain a coefficient estimate $\hat{\beta}_t$ and hence forecasts for total returns in the next month. The strategy then makes an investment of $\hat{\beta}_t' x_t$ in the bond in question (this would be a short position if it is a negative number) and holds that for month $t+1$, before rebalancing again in the same way.

(ii) At the end of each month, regression (2) is run to obtain forecasts for announcement-window returns in the next month. In the subsequent month, at the time of any macroeconomic news announcement, the strategy then makes an investment of $\hat{\beta}_{A,t}' x_t$ in the bond in question five minutes before the announcement, and sells this ten minutes after the announcement.

(iii) At the end of each month, regression (3) is run to obtain forecasts for non-announcement-window returns in the next month. In the next month, the strategy then makes an investment of $\hat{\beta}_{NA,t}' x_t$, except sells this position five minutes before each announcement, only to buy it back ten minutes after the announcement.

(iv) At the end of each month, regression (2) is run to obtain forecasts for announcement-window returns in the next month. The strategy then makes an investment of $\hat{\beta}_{A,t}' x_t$ in

[5] Note, these trading strategy results are only approximate: while transactions costs are taken account of later in the section, we ignore the effects of margin requirements. Further, for the strategies that are not invested at all times accumulated gains could be reinvested and accumulated losses would have to be financed. We have neglected these issues.

the bond in question and holds it for the entire month.

We compute the annualized out-of-sample Sharpe ratio associated with these four strategies. In each case, the strategies are evaluated recursively, with the first forecast made for January 1995, using data only through December 1994, and the sample period is then rolled forward one month at a time for a total of 13 years of out-of-sample observations. A percentile-t bootstrap is used to test the hypothesis that the population Sharpe ratios are zero and that the Sharpe ratios using the first strategy is equal to that using each of the other three.

The results are shown in Table 5. The Sharpe-ratio results paint a similar picture to the mean-square error results in the previous subsection. The Sharpe ratios for the ordinary portfolio in (i) are all estimated to be negative. But the Sharpe ratios for the announcement window portfolios are positive. The difference is statistically significant for ten- and thirty-year bond futures, and is borderline significant for five-year futures. The hybrid strategy (iv) also gives a significant positive Sharpe ratio. All this indicates that expected excess bond returns are so poorly estimated outside of announcement windows that the investor is best off discarding these data in forecasting future returns.

This result is closely related to the results of Faust and Wright (2008) regarding efficient predictive regressions. The main point of that work is that if there is some component of the variable being predicted that is thought to be unpredictable and is *ex post* measurable, then removing that component will tend to improve precision. In the same way, removing the non-announcement window returns appears to allow the relationship between returns and the predictors to be more precisely estimated.returns.

*3.3 Transactions Costs*

One might wonder what transactions costs might do to this strategy. Transactions costs are low in futures markets. Still a strategy that calls for buying and selling a position every time an announcement comes out will require a lot of trading. To address this question, we assumed that the trading cost is half a tick for the five- and ten-year futures contracts, and a whole tick for the thirty-year contract (these are close to the interdealer estimates of Fleming and Sarkar (1999)).[6] We then adjusted the returns of the four strategies for transactions costs. The resulting Sharpe ratios are shown in Table 6.

Transactions costs wipe out any gain from the trading strategy of entering into the positions only around times of news announcements (strategy (ii)). Inclusive of transactions costs, the Sharpe ratios for this strategy are negative, and either not significantly different from those for the ordinary portfolio in (i), or significantly *lower*. This does not make this strategy irrelevant to investors–if an investor was planning to buy or sell a futures position around the time of the news announcement anyway, then the results exclusive of transactions costs give this investor advice on the optimal timing of when to do the trade. It does however mean that an investor could not expect positive returns from exploiting this strategy alone. However, the "hybrid" strategy involves much less frequent trading and accordingly the transactions costs barely affects the Sharpe ratio of this strategy which remains positive and significantly different from the Sharpe ratio for the ordinary portfolio in (i).

## 4. Interpretation and implications

The most conventional explanation of predictable excess returns is that they reflect time variation payment for bearing risk. As noted above, we think the announcement window returns are best viewed as price jumps associated with the arrival of discrete lumps of macro news. Piazzesi (2005, 2009) provides one formalization of this phenomenon using an affine term structure model in which the state vector follows a diffusion process with jumps of random magnitude but deterministic times. For concreteness, we sketch her framework and discuss the interpretation of our results in this context.

[6] A tick is 1/32nd. So a bid-ask spread of one tick means that the spread is 3.125 cents on a bond with a face value of $100.

Suppose that the state vector, $x(t)$ follows a jump diffusion

$$dx(t) = \mu_x(x(t^-))dt + \sigma_x(x(t^-))dB(t) + J(t)dN(t)$$

where $B(t)$ is a standard Brownian motion, $J(t)$ is a random jump size, and $N(t)$ is a counter for deterministic jumps. Assume also that the short-term interest rate is an affine function of the state vector: $r(t) = \delta_0 + \delta_1' x(t)$, and that the pricing kernel follows a jump diffusion:

$$\tfrac{dM(t)}{M(t^-)} = -r(t)dt - \tfrac{d\xi(t)}{\xi(t^-)}$$

with

$$\tfrac{d\xi(t)}{\xi(t^-)} = \lambda(x(t))'dB(t) + J_M(x(t^-), \Delta x\,(t))dN(t)$$

where the elements of $\lambda(x(t))$ represent the market prices of the Brownian motions and $J_M(x(t^-), \Delta x(t))$ represents the market price of jump risk.

Let $R(t)$ denote the return on a bond at the instant of a jump. As Piazzesi verifies, under the risk-neutral measure, it must be that $E^*_{t-}(R(t)) = 0$—an expected jump in price (under the risk neutral measure) seen from an instant before would be a very good deal. Of course, the predictability results above are under the physical measure, which Piazzesi shows must satisfy,

$$E_{t^-}(R(t)) = -E_{t^-}(J_M(x(t^-), \Delta x(t))R(t)) \tag{4}$$

The fact that returns at non-announcement times are not predictable implies that the market price of the diffusive component of risk, $\lambda$, is zero. And the fact that returns around the deterministic jump times are predictable represents direct evidence that the market price of jump risk is non-zero and is state-dependent. The risk-adjustment density $\xi(t)$ jumps at times of macroeconomic news announcements because if $J_M(x(t^-), \Delta x(t))$ is not random conditional on the information set right before the jump time, then the only solution to (4) can be $E_{t^-}(R(t)) = 0$ and $J_M$ must be state-dependent because otherwise the only solution to this last equation is for a constant expected return. Our results provide support to the model of Johannes (2004), who constructed a one factor model in which only jump risk was priced.

This seems at least a tantalizing clue that it is the pricing of risk about the state of the economy that drives time variation in risk premia. It also provides additional evidence against the practice of interpreting these jumps as reflecting changes in expectations and helps to explain the puzzle of why bond prices are far more volatile at times of macroeconomic news announcements than many of us think can plausibly be explained by revisions to future expectations of short-term interest rates. However, this framework does not give any general equilibrium account of where the prices of risk are coming from and so it does not tell us exactly what agents are learning about the economy through news announcements that makes them demand risk premia to hold long-term bonds.

Setting aside the economic interpretation, the results above also suggest new avenues for studying predictability of returns. It is generally agreed that predictive power will be low and, given the modest available sample sizes, precision of estimated coefficients is likely to be an issue. From the standpoint of rejecting the null hypothesis of no predictability, this means that power will be low. From the standpoint of profitably exploiting the information, this lack of precision will raise the mean squared error of returns.

Splitting returns into different components based on objective criteria and then modelling the components separately appears to be one way to raise precision. Perhaps the most famous example of this kind of work is the early work on the January effect. This work suggests that the announcement window cut of the data may be important. Other cuts may also be of interest. Further, we predictors that have been shown to work for the full returns and showed that they are most strongly related to a single identifiable component. It may well be that there are useful predictors for individual components that simply wash out when applied to the full returns. Thus, more complete examination of different cuts and different predictors may be in order. Of course, this raises all the vexing questions about data snooping and the validity of the results. But these problems are no different in their manifestations than in many other areas of the literature's broad-ranging search for predictability.

## 5. Conclusion.

There is a good body of evidence that bond returns are somewhat predictable. Moreover, much of the volatility of assets, especially bonds, occurs in short windows around news announcements. This motivates the question of whether the predictable returns are earned at times of news announcements, at other times, or both. This paper has found that the significant predictability can only be found at times of news announcements. This means that the risk associated with jumps around news announcements is priced, but that the continuous component of volatility is not. It also motivates consideration of a trading strategy that uses only forecasts of announcement-window returns to determine the position to take, on the grounds that the signal-to-noise ratio is more favorable for announcement-window returns.

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Table 1A: Returns on Five-year futures

| | Total | 8:30 | Non-8:30 | Total | 8:30 | Non-8:30 |
|---|---|---|---|---|---|---|
| | | | One-month Returns | | | |
| PC1 | 0.03 | 0.01 | 0.03 | 0.03 | 0.01 | 0.03 |
| | (0.04) | (0.02) | (0.04) | (0.04) | (0.02) | (0.04) |
| PC2 | -0.56** | -0.22*** | -0.35* | -0.57*** | -0.22*** | -0.35* |
| | (0.22) | (0.08) | (0.21) | (0.22) | (0.08) | (0.20) |
| PC3 | 0.67 | -0.88 | 1.55 | 0.57 | -0.91 | 1.48 |
| | (1.71) | (0.58) | (1.61) | (1.74) | (0.58) | (1.63) |
| PC4 | | | | -5.58 | -0.33 | -5.25 |
| | | | | (3.65) | (1.26) | (3.35) |
| PC5 | | | | 8.11 | 3.23* | 4.88 |
| | | | | (5.88) | (1.83) | (5.50) |
| p-val | 0.040 | 0.007 | 0.131 | 0.024 | 0.012 | 0.146 |
| $R^2$ | 0.030 | 0.038 | 0.020 | 0.050 | 0.049 | 0.035 |
| $\beta_A = \beta_{NA}$ | 0.378 | | | 0.399 | | |
| | | | Cumulative Six-Month Returns | | | |
| PC1 | 0.29** | 0.05 | 0.24* | 0.29** | 0.05 | 0.24* |
| | (0.13) | (0.06) | (0.13) | (0.13) | (0.06) | (0.13) |
| PC2 | -3.67*** | -1.29*** | -2.38** | -3.71*** | -1.31*** | -2.41** |
| | (1.11) | (0.28) | (1.12) | (1.08) | (0.29) | (1.10) |
| PC3 | -6.49 | -4.48** | -2.01 | -6.92 | -4.60** | -2.32 |
| | (6.10) | (2.04) | (6.55) | (5.95) | (2.06) | (6.42) |
| PC4 | | | | -20.22* | -0.96 | -19.26 |
| | | | | (12.57) | (3.33) | (13.66) |
| PC5 | | | | 17.90 | 6.56 | 11.34 |
| | | | | (14.32) | (4.56) | (15.64) |
| p-val | 0.000 | 0.000 | 0.027 | 0.000 | 0.000 | 0.002 |
| $R^2$ | 0.207 | 0.239 | 0.105 | 0.234 | 0.249 | 0.129 |

This table shows the coefficients from regressions of five-year bond futures returns, cumulative returns in 15-minute windows bracketing announcements (8:30) and the remainder of returns (non-8:30) onto the principal components of the term structure of interest rates at the end of the month before the holding period. Results are shown where the regressors are either one-month returns, or cumulative six-month returns, along with White standard errors and Newey-West standard errors, respectively. Corresponding p-values testing the hypothesis that the slope coefficients are jointly zero, and $R^2$ values, are included. The row labelled $\beta_A = \beta_{NA}$ reports the p-value testing the cross-equation restriction that the slope coefficients are equal in announcement and non-announcement windows.

Table 1B: Returns on Ten-year futures

| | Total | 8:30 | Non-8:30 | Total | 8:30 | Non-8:30 |
|---|---|---|---|---|---|---|
| | | | One-month Returns | | | |
| PC1 | 0.05 | 0.00 | 0.04 | 0.05 | 0.00 | 0.05 |
| | (0.06) | (0.02) | (0.05) | (0.06) | (0.02) | (0.05) |
| PC2 | -0.75** | -0.27*** | -0.48* | -0.76** | -0.27*** | -0.49* |
| | (0.31) | (0.10) | (0.29) | (0.31) | (0.10) | (0.29) |
| PC3 | 0.57 | -1.88** | 2.46 | 0.44 | -1.93** | 2.37 |
| | (2.44) | (0.76) | (2.29) | (2.48) | (0.77) | (2.32) |
| PC4 | | | | -6.07 | -0.59 | -5.48 |
| | | | | (5.26) | (1.74) | (4.87) |
| PC5 | | | | 10.29 | 4.40 | 5.90 |
| | | | | (9.42) | (2.42) | (8.80) |
| p-val | 0.064 | 0.004 | 0.119 | 0.043 | 0.006 | 0.169 |
| $R^2$ | 0.026 | 0.043 | 0.021 | 0.040 | 0.055 | 0.030 |
| $\beta_A = \beta_{NA}$ | 0.160 | | | 0.291 | | |
| | | | Cumulative Six-Month Returns | | | |
| PC1 | 0.33* | 0.02 | 0.31 | 0.33* | 0.01 | 0.33 |
| | (0.18) | (0.09) | (0.18) | (0.19) | (0.09) | (0.19) |
| PC2 | -4.83*** | -1.42*** | -3.41** | -4.89*** | -1.44*** | -3.45** |
| | (1.44) | (0.38) | (1.51) | (1.42) | (0.39) | (1.50) |
| PC3 | -11.63 | -7.96*** | -3.68 | -12.20 | -8.13*** | -4.07 |
| | (8.01) | (3.05) | (8.91) | (7.86) | (3.07) | (8.81) |
| PC4 | | | | -15.39 | -2.03 | -13.36 |
| | | | | (17.44) | (4.59) | (19.29) |
| PC5 | | | | 26.88 | 8.76 | 18.12 |
| | | | | (20.04) | (6.75) | (22.81) |
| p-val | 0.001 | 0.000 | 0.013 | 0.000 | 0.001 | 0.016 |
| $R^2$ | 0.192 | 0.193 | 0.109 | 0.207 | 0.203 | 0.118 |

As for Table 1A, except for ten-year futures returns.

Table 1C: Returns on Thirty-year futures

| | Total | 8:30 | Non-8:30 | Total | 8:30 | Non-8:30 |
|---|---|---|---|---|---|---|
| | | | One-month Returns | | | |
| PC1 | 0.08 | 0.00 | 0.08 | 0.09 | 0.00 | 0.08 |
| | (0.09) | (0.03) | (0.08) | (0.09) | (0.03) | (0.08) |
| PC2 | -1.04** | -0.32** | -0.73* | -1.05** | -0.32** | -0.74* |
| | (0.42) | (0.13) | (0.39) | (0.41) | (0.13) | (0.39) |
| PC3 | 0.58 | -3.52*** | 4.10 | 0.45 | -3.57*** | 4.01 |
| | (3.54) | (1.03) | (3.38) | (3.56) | (1.04) | (3.39) |
| PC4 | | | | -2.43 | 0.02 | -2.45 |
| | | | | (7.50) | (2.30) | (7.00) |
| PC5 | | | | 13.21 | 5.08 | 8.13 |
| | | | | (11.93) | (3.28) | (11.25) |
| p-val | 0.050 | 0.001 | 0.066 | 0.084 | 0.001 | 0.172 |
| $R^2$ | 0.026 | 0.060 | 0.025 | 0.033 | 0.068 | 0.029 |
| $\beta_A = \beta_{NA}$ | 0.052 | | | 0.160 | | |
| | | | Cumulative Six-Month Returns | | | |
| PC1 | 0.46 | -0.04 | 0.50 | 0.46* | -0.04 | 0.50* |
| | (0.27) | (0.11) | (0.27) | (0.28) | (0.11) | (0.28) |
| PC2 | -6.55*** | -1.39*** | -5.16** | -6.61*** | -1.41*** | -5.21** |
| | (1.81) | (0.53) | (2.02) | (1.79) | (0.54) | (2.00) |
| PC3 | -16.62 | -13.66*** | -2.95 | -17.19* | -13.80*** | -3.39 |
| | (10.26) | (3.97) | (11.65) | 10.19 | (4.01) | (11.64) |
| PC4 | | | | 6.44 | -1.77 | 8.21 |
| | | | | (24.30) | (6.61) | (27.88) |
| PC5 | | | | 33.86 | 7.07 | 26.79 |
| | | | | (27.67) | (9.03) | (31.97) |
| p-val | 0.000 | 0.000 | 0.008 | 0.000 | 0.003 | 0.029 |
| $R^2$ | 0.183 | 0.194 | 0.117 | 0.191 | 0.198 | 0.123 |

As for Table 1A, except for thirty-year futures returns.

Table 1D: Returns on S&P Futures

| | Total | 8:30 | Non-8:30 | Total | 8:30 | Non-8:30 |
|---|---|---|---|---|---|---|
| DY | 3.64*** | -0.17 | 3.81*** | 4.59*** | -0.25 | 4.84*** |
| | (1.35) | (0.49) | (1.29) | (1.35) | (0.53) | (1.29) |
| VRP | | | | 0.05*** | -0.00 | 0.06*** |
| | | | | (0.02) | (0.01) | 0.02 |
| p-val | 0.008 | 0.732 | 0.004 | 0.000 | 0.767 | 0.000 |
| $R^2$ | 0.039 | 0.001 | 0.046 | 0.078 | 0.004 | 0.096 |
| | | | Cumulative Six-Month Returns | | | |
| DY | 21.67*** | -0.16 | 21.84 | 25.68*** | 0.45 | 25.23*** |
| | (6.68) | (3.24) | (5.43) | (6.38) | (3.19) | (5.29) |
| VRP | | | | 0.23*** | 0.03 | 0.19*** |
| | | | | (0.04) | (0.02)* | (0.04) |
| p-val | 0.001 | 0.960 | 0.000 | 0.000 | 0.260 | 0.000 |
| $R^2$ | 0.237 | 0.000 | 0.283 | 0.359 | 0.023 | 0.386 |

This table shows the coefficients from regressions of S&P futures returns, total cumulative returns in fifteen-minute windows bracketing announcements and the remainder of returns onto the log dividend yield and the variance risk premium of Bollerslev, Tauchen and Zhou (2009) at the end of the month before the holding period. Results are shown where the regressors are either one-month returns, or cumulative six-month returns, along with White standard errors for the one-month returns and Newey-West standard errors for the six-month returns. Corresponding p-values testing the hypothesis that the slope coefficients are jointly zero, and $R^2$ values, are included.

Table 2: Ratio of announcement return variance to total return variance
(Both returns and expected returns are decomposed)

| | Five-year futures | Ten-year futures | Thirty-year futures | S&P futures |
|---|---|---|---|---|
| Returns | 0.140 | 0.132 | 0.111 | 0.077 |
| Expected | 0.180 | 0.226 | 0.263 | 0.004 |

The first row of the table shows the ratio of the sample variance of returns bracketing news announcements to the sample variance of total returns. The second row shows the ratio of the sample variance of expected returns bracketing news announcements to the sample variance of total expected returns, where the expectations are formed from the regressions in Table 1, using PC1-PC3 as the regressors (for bonds) or both the log dividend yield and the variance risk premium (for stocks).

Table 3: Predicting Ten-year Futures Returns around Individual Announcements

| | CPI | DGO | GDP | HS | ICLM | NFPAY | PI | PPI | RS | TBAL | IP | FF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | One-month Returns | | | | | | |
| PC1 | 0.00 | -0.00 | -0.00 | 0.00 | 0.02 | -0.01 | -0.00 | 0.00 | 0.02** | -0.00 | -0.01 | -0.00 |
| | (0.01) | (0.01) | (0.01) | (0.00) | (0.01) | (0.02) | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.01) |
| PC2 | 0.01 | 0.02 | -0.03 | 0.02 | -0.08 | -0.12* | 0.02 | -0.11*** | -0.03 | -0.02 | -0.02 | -0.02 |
| | (0.04) | (0.03) | (0.03) | (0.03) | (0.05) | (0.08) | (0.02) | (0.04) | (0.04) | (0.02) | (0.02) | (0.03) |
| PC3 | -0.40 | -0.40* | 0.06 | -0.18 | -0.86* | -0.19 | 0.10 | -0.57* | -0.79** | -0.10 | 0.10 | 0.32 |
| | (0.27) | (0.21) | (0.24) | (0.18) | (0.41) | (0.59) | (0.17) | (0.31) | (0.31) | (0.14) | (0.16) | (0.25) |
| p-val | 0.486 | 0.191 | 0.849 | 0.484 | 0.014 | 0.417 | 0.813 | 0.008 | 0.005 | 0.746 | 0.306 | 0.539 |
| | | | | | | Cumulative Six-Month Returns | | | | | | |
| PC1 | -0.01 | -0.02 | -0.00 | 0.01 | 0.10*** | -0.02 | -0.01 | 0.02 | 0.09*** | -0.02 | -0.40*** | -0.00 |
| | (0.03) | (0.02) | (0.01) | (0.03) | (0.04) | (0.04) | (0.01) | (0.03) | (0.03) | (0.02) | (0.01) | (0.02) |
| PC2 | 0.08 | 0.20* | -0.29** | 0.06 | -0.45** | -0.74* | 0.13 | -0.45*** | -0.14 | -0.06 | -0.07 | -0.11 |
| | (0.14) | (0.12) | (0.13) | (0.10) | (0.19) | (0.42) | (0.09) | (0.13) | (0.15) | (0.09) | (0.07) | (0.13) |
| PC3 | -2.42** | -0.73 | -1.40 | -2.17** | -3.40** | -0.26 | 0.41 | -0.58 | -3.10*** | 0.11 | 0.93* | 0.16 |
| | (0.97) | (0.78) | (0.92) | (0.86) | (1.41) | (1.86) | (0.66) | (1.25) | (1.18) | (0.60) | (0.51) | (0.74) |
| p-val | 0.081 | 0.122 | 0.008 | 0.025 | 0.000 | 0.341 | 0.376 | 0.001 | 0.000 | 0.626 | 0.001 | 0.832 |

This table reports the regression of one-month and six-month cumulative returns from 5 minutes before each announcement type to 10 minutes after on the first three principal components of the yield curve at the start of the previous month. The mnemonics for the announcements are DGO: Durable Goods Orders. HS: Housing Starts, ICLM: Initial Claims, NFPAY: Non-Farm Payrolls, PI: Personal Income, RETLS: Retail Sales, TBAL: Trade Balance, IP: Industrial Production and FF: Federal Funds rate.

Table 4: Out-of-Sample Relative Mean-Square Errors of Forecasts of Bond Futures Returns

| | Five-year | Ten-year | Thirty-year |
|---|---|---|---|
| Predictors: First Three Principal Components | | | |
| Total | 1.07 | 1.07 | 1.06 |
| *p-val* | *0.78* | *0.82* | *0.76* |
| Announcement Window | 0.99 | 0.97 | 0.95 |
| *p-val* | *0.06* | *0.01* | *0.00* |
| Non-Announcement Window | 1.10 | 1.10 | 1.08 |
| *p-val* | *0.90* | *0.89* | *0.83* |
| Predictors: First Five Principal Components | | | |
| Total | 1.08 | 1.09 | 1.09 |
| *p-val* | *0.70* | *0.79* | *0.81* |
| Announcement Window | 1.00 | 0.98 | 0.95 |
| *p-val* | *0.12* | *0.04* | *0.00* |
| Non-Announcement Window | 1.12 | 1.12 | 1.11 |
| *p-val* | *0.85* | *0.87* | *0.86* |

Notes: This table reports the out-of-sample relative mean-square error of one-step-ahead forecasts based on estimation of equations (1), (2) and (3), relative to their counterparts imposing that the slope coefficient is equal to zero, and estimating the intercept alone. The results are given in the rows labeled *total*, *announcement window*, and *non-announcement window*, respectively. Forecasts are made recursively, starting in January 1995, up to the end of the sample in December 2007. The p-values are based on comparing the test statistic of Diebold and Mariano (1995) with the asymptotic critical values of Clark and McCracken (2005), suitable for the case of a nested forecast comparison.

Table 5: Annualized Out-of-Sample Sharpe Ratios of Bond Futures Portfolios

| | Five-year | Ten-year | Thirty-year |
|---|---|---|---|
| Predictors: First Three Principal Components | | | |
| Total | -0.17 | -0.26 | -0.43 |
| Announcement Window | 0.36 | 0.58 | 0.91 |
| Non-Announcement Window | -0.33 | -0.41 | -0.45 |
| Hybrid | 0.50 | 0.50 | 0.54 |
| *Bootstrap p-val* | | | |
| $H_0$: Total=Announcement | 0.14 | 0.01 | 0.00 |
| $H_0$: Total=Non-Announcement | 0.37 | 0.40 | 0.88 |
| $H_0$: Total=Hybrid | 0.05 | 0.02 | 0.02 |
| Predictors: First Five Principal Components | | | |
| Total | -0.01 | -0.18 | -0.44 |
| Announcement Window | 0.31 | 0.54 | 0.85 |
| Non-Announcement Window | -0.21 | -0.35 | -0.50 |
| Hybrid | 0.53 | 0.52 | 0.49 |
| *Bootstrap p-val* | | | |
| $H_0$: Total=Announcement | 0.37 | 0.03 | 0.00 |
| $H_0$: Total=Non-Announcement | 0.26 | 0.28 | 0.62 |
| $H_0$: Total=Hybrid | 0.07 | 0.01 | 0.00 |

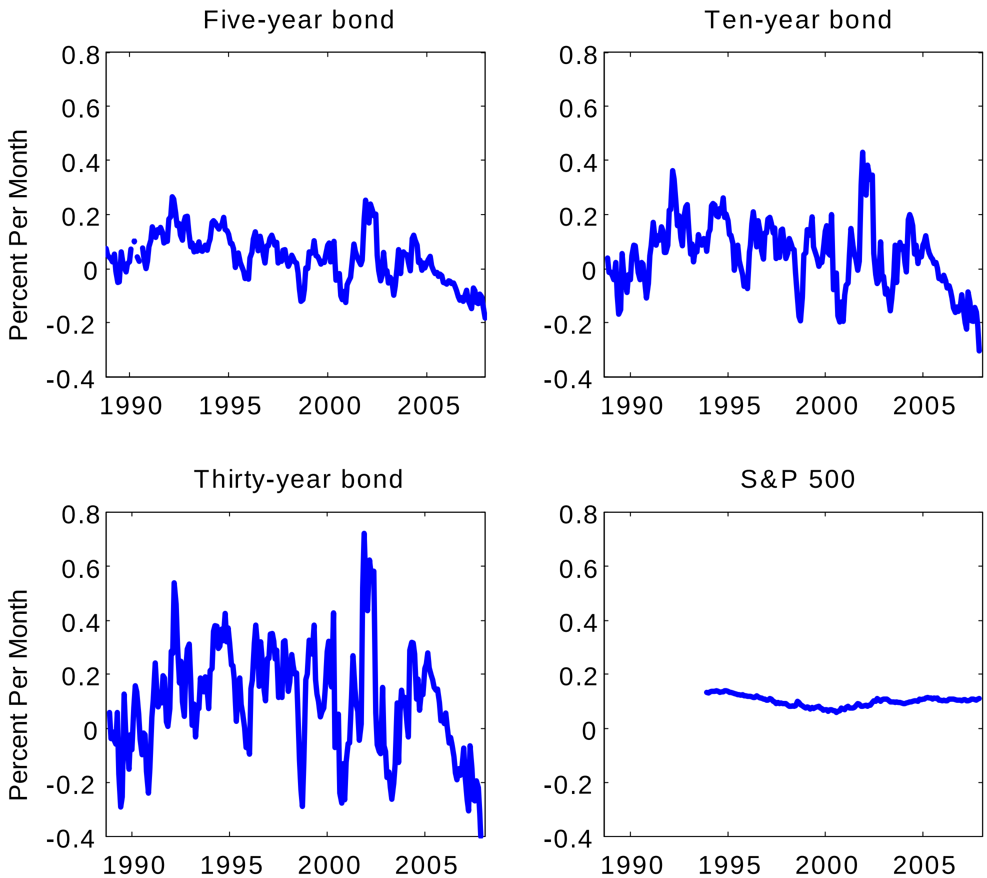
Notes: The rows labeled *total*, *announcement window*, and *non-announcement window* give the realized Sharpe ratios of a portfolio that makes an investment in the bond futures contract during the whole month, during announcement windows only, and during non-announcement windows only, respectively, where the size of the investment is the real-time *ex-ante* predicted return for that window as computed at the end of the previous month. The row labeled *hybrid* gives the realized Sharpe ratio of a portfolio that is held for the whole month, but where the size of the investment is the real-time *ex-ante* predicted return for the announcement window only. Predicted returns are calculated recursively, starting in January 1995, up to the end of the sample in December 2007. If the predicted returns are negative, it is a short position. No allowance is made for transactions costs. The p-values are percentile-t bootstrap p values testing the hypothesis that the Sharpe ratios for the total returns are equal to those in the other windows. All Sharpe ratios are annualized.

Table 6: Annualized Out-of-Sample Sharpe Ratios of Bond Futures Portfolios Including Transactions Costs

| | Five-year | Ten-year | Thirty-year |
|---|---|---|---|
| Predictors: First Three Principal Components | | | |
| Total | -0.17 | -0.26 | -0.43 |
| Announcement Window | -0.85 | -0.34 | -0.48 |
| Non-Announcement Window | -0.74 | -0.68 | -0.85 |
| Hybrid | 0.49 | 0.50 | 0.53 |
| *Bootstrap p-val* | | | |
| $H_0$: Total=Announcement | 0.05 | 0.81 | 0.90 |
| $H_0$: Total=Non-Announcement | 0.00 | 0.02 | 0.01 |
| $H_0$: Total=Hybrid | 0.05 | 0.03 | 0.02 |
| Predictors: First Five Principal Components | | | |
| Total | -0.02 | -0.18 | -0.44 |
| Announcement Window | -0.92 | -0.35 | -0.49 |
| Non-Announcement Window | -0.63 | -0.62 | -0.85 |
| Hybrid | 0.52 | 0.52 | 0.48 |
| *Bootstrap p-val* | | | |
| $H_0$: Total=Announcement | 0.01 | 0.65 | 0.90 |
| $H_0$: Total=Non-Announcement | 0.00 | 0.01 | 0.01 |
| $H_0$: Total=Hybrid | 0.07 | 0.01 | 0.00 |

Notes: As in Table 4, except that transactions costs are allowed for. The transactions costs are assumed to be equal to half of one tick for the five- and ten-year contracts, and one tick for the thirty-year contract. The tick size is 1/32 where the face value is \$100, meaning 3.125 cents per \$100.

Figure 1: Predicted Announcement-Window Returns from Estimating Equation (2)




Notes: This figure shows the fitted values from the estimation of equation (2).