Forecasting Government Bond Risk Premia Using Technical Indicators

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Abstract

While economic variables have been used extensively to forecast the U.S. bond risk premia, little attention has been paid to the use of technical indicators which are widely employed by practitioners. In this paper, we fill this gap by studying the predictive ability of using a variety of technical indicators vis-á-vis the economic variables. We find that the technical indicators have significant both in- and out-of-sample forecasting power, and utilizing information from both technical indicators and economic variables increases the substantially the forecasting performances relative to using just economic variables. Moreover, we find that the economic value of the bond risk premia forecasts are only comparable to that of the equity risk premium forecasts, despite the R^2s in the bond market are more than 10 times greater than those in the stock market.

JEL classifications: C53, C58, G11, G12, G17

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1 Introduction

There are a number of studies that use various financial and macroeconomic variables to predict the excess returns, bond risk premia, on the U.S. government bonds. For examples, while Fama and Bliss (1987) provide evidence that the n-year forward spread predicts n-year bond risk premia, Keim and Stambaugh (1986), Fama and French (1989), and Campbell and Shiller (1991) show that yield spreads have such predictive power too; Ilmanen (1995) find bond risk premia predictability across countries using macroeconomic variables, and Baker, Greenwood, and Wurgler (2003) detect the predictability with the use of the maturity of new debt issues. Recently, based on a linear combination of five forward rates, Cochrane and Piazzesi (2005) find a much higher predictive R^2, between 30% and 35%, for the risk premia on short-term bonds with maturities ranging from two to five years. Ludvigson and Ng (2009) demonstrate further that the impressive predictive power found by Cochrane and Piazzesi (2005) can be improved with additional five macroeconomic factors estimated from a set of 132 macroeconomic variables that measure a wide range of economic activities.

In this paper, we study the predictive power on the bond risk premia of a new set of predictors, the technical indicators (past price patterns)in the bond and stock markets. Studies that use of technical indicators in the equity market goes at least to Cowles (1933). Brock, Lakonishok, and LeBaron (1992), Bessembinder and Chan (1998), Lo, Mamaysky, and Wang (2000), Han, Yang, and Zhou (2012), and Neely, Rapach, Tu and Zhou (2012), among others, find that technical indicators have significant forecasting power on the equity risk premium, which may help understand why technical indicators are widely employed to discern market price trends by traders and investors (e.g., Schwager, 1993, 1995; Billingsley and Chance, 1996; Covel, 2005; Park and Irwin, 2007; Lo and Hasanhodzic, 2010).[1] However, to our knowledge, there are no academic studies that examine the the predictive power of the technical indicators in the bond market. In filling this gap, we seek to answer two questions: (1) Do technical indicators provide useful information for forecasting bond risk premia? (2) Can technical indicators be used in conjunction with economic predictors, such as forward rates and macroeconomic variables, to improve bond risk premia predictability? Moreover, extending to the earlier studies of Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) on short-term bonds, we study in this paper also the predictability

[1] In foreign exchange markets, academic studies generally find stronger support for the predictability of technical analysis. For example, Neely, Weller, and Dittmar (1997), LeBaron (1999) and Neely (2002) show that moving averages generate substantial portfolio gains for currency trading. Moreover, Menkhoff and Taylor (2007) argue that technical analysis today is as important as fundamental analysis to currency mangers.

of long-term government bond risk premium with maturities ranging from 17 to 20 years.

We use a total of 63 technical indicators. The first 48 technical indicators are constructed in the standard way of technical analysis based on the forward spread moving averages. Since the bond market trading volume data are unavailable to us, we construct the next 15 technical indicators based on stock market trading volume.[2] Given that the stock and bond market are closely related (e.g., Fama and French, 1989; Lander, Orphanides and Douvogiannis, 1997; Campbell and Vuoltenaho, 2004; Goyenko and Ukhov, 2009; Bekaert and Engstrom, 2010), the volume technical indicators serve as a proxy for those bond volume indicators used in practice. Hence, we have a total of 63 technical indicators. Econometrically, including such a large number of technical indicators in a predictive regression model simultaneously makes in-sample over-fitting a great concern, which is likely to deliver poor out-of-sample forecasts.[3] To avoid model over-fitting, we, following Ludvigson and Ng (2007, 2009), generate bond risk premia forecasts based on only a small number of principal component (PC) factors extracted from the set of 63 technical indicators.

We analyze the predictability both in- and out-of-sample. In our in-sample analysis, we examine first the predictive ability of using technical indicators alone in a factor-augmented predictive regression framework. Then, we investigate whether the technical indicators contain incremental predictive information beyond that of using CP_t and LN_t, the predictors of Cochrane and Piazzesi's (2005) and Ludvigson and Ng's (2009), respectively. Our in-sample analysis reveals a strong predictive power of the technical indicators. With data from January 1964 to December 2007, while CP_t and LN_t each has R^2 range of 31–36% and 14–23%, respectively, the set of technical indicators alone has an R^2 range of 28–32%, for the short-term government bonds. Strikingly, for long-term government bonds, the in-sample R^2 of LN_t diminishes greatly to about 5%, but the R^2 of CP_t is still higher than 27%. Surprisingly, the technical indicator factors, selected to best predict the short-term bond risk premium, have R^2s even slightly higher before, about 45% for all the long-term maturities. When utilizing information from both technical indicators and economic variables, the resulting forecasts perform the best, with R^2s in the range of 46–47%, for both short- and long-term bonds.

Out-of-sample tests, however, seem to be a more relevant standard for assessing genuine return predictability in real time, as argued by Goyal and Welch (2008), among others, in the context of the stock market prediction.[4] We study the out-of-sample predictive ability of technical indicators

[2]However, we do not examine the technical indicators based on stock market moving averages as they are dominated by the same moving averages based on bond dada.

[3]For instance, Hansen (2009) finds that good in-sample fit is often related to poor out-of-sample performance.

[4]See Lettau and Ludvigson (2009), e.g., for a review on in-sample versus out-of-sample asset return predictability.

based on the Campbell and Thompson's (2008) out-of-sample R^2 statistic, R^2_{OS}, which measures the percentage reduction in the mean squared predictive error. Following most out-of-sample studies, we transform the technical factors into bond risk premia forecasts using a recursive predictive regression model, and calculate R^2_{OS} statistics for the competing out-of-sample forecasts based on technical indicator factor, $\tilde{F}_t$, relative to historical average benchmark. In the recursive procedure, at any time t, we implement the predictive regressions with all predictors, such as $\tilde{F}_t$, CP_t, and LN_t, using information available only up to t. This avoids the look-ahead bias or the use of future information.

As is the case for the equity market, out-of-sample evidence is generally weaker than the in-sample one. For short-term bond, the R^2_{OS}s of the technical indicators are now in the range of 25–26%, lower than the 28–32% range of the in-sample R^2. Similarly, the forecasts based on CP_t also have lower R^2_{OS}s in the 15–18% range. In addition, the forecasts based on LN_t have R^2_{OS}s of only 4.7%, 0.1%, -1.4% and -4.2%, respectively, for maturities varying from 2 to 5 years. Nevertheless, when all the predictors are combined, the R^2_{OS}s improve substantially, to the 31–33% range. For long-term bonds, the same conclusion is true qualitatively, but the performance with all the predictors come down to to the 20–24% range.

Statistically, both the in- and out-of-sample evidence is greatly significant. The open question is whether the statistical significance is of economic significance. To assess the economic value of the out-of-sample bond risk premia forecasts, following Kandel and Stambaugh (1996) and Pástor and Stambaugh (2000) and many others, we examine the utility gains from an asset allocation problem. Specially, we consider an investor who optimally allocates a portfolio between an n-year Treasury bond and one-year risk-free Treasury bill. To do so, we assume a mean-variance utility function for simplicity as in Campbell and Thompson (2008), among others. We calculate the average utility gain of the investor when he/she forms portfolios using the out-of-sample excess bond return forecasts generated by some or all of the predictors versus ignoring the forecasts. While numerous studies that investigate the profitability of technical indicators in the equity market are *ad hoc*, not taking into account for the role played by the investor's risk aversion. In contrast, similar to Zhu and Zhou (2009) and Neely, Rapach, Tu and Zhou (2011), we avoid this drawback with use of the utility function.

Empirically, we find that, if the risk aversion coefficient is 3, then the investor is willing to pay an annualized portfolio management fee of 2.5%, over the time period 1975:01$-$2007:12, to have access to the 5-year bond return forecast utilizing the information contained in all the predictors. If the technical indicators were excluded, the fee would drop to 0.92%. But over the 1985:01−2007:12 period, the fee can be as high as 4.21%. However, for the the longer bonds over the available 1985:01−2007:12 period, the value is fairly limited, and are in the 0.55–0.97% range. In this case, the importance of technical indicators becomes more apparent. Without them, the fee for the long-term bond would drop to a undesirable range of -0.67–0.01%.

The economic value assessment is interesting in understanding why the bond market is much more predictable than the stock market in terms of R^2 (e.g., Della Corte, Sarno, and Thornton 2008; Thornton and Valente, 2012). In the stock market, as reported by the latest study of Neely, Rapach, Tu and Zhou (2011), the maximum monthly out-of-sample R^2_{OS} is about 1.66%, and maximum annual out-of-sample utility gain is 5.32%. Hence the bond market is 10 times or more predictable than the stock market. But our economic value assessment reveals that the bond market is not 10 times profitable than the stock market, suggesting across the financial markets, the economic value of forecasting is likely to be the same due to perhaps across market arbitrage or intermarket efficiency.

Overall, the predictive power of the technical predictors on the bond risk premia is substantial. What useful information beyond that measured by the macroeconomic variables do the technical predictors contain? There appear at least two intuitive explanations for the additional information. First, the set of the macroeconomic variables is clearly not exhaustive, and ignores important variables such as government policy changes and the large shocks in the world economy. However, any persistent reaction of the bond market to the latter variables will be reflected by the technical indicators. Second, the technical indicators capture anticipated future events. For example, on the recent Fed QE3 on January 13, 2012, the long-term bond future price dropped 6 days out of 7, with one day virtually unchanged. The reason is that, as put by Aneiro in Barron's, "Market had priced in expectations of some form of a third round of quantitative easing ahead of the Fed's policy-committee meeting."[5] The example illustrates that price patterns or technical indicators are forward looking that can capture the market expectation of the yet to be released macroeconomic variables or future events to unravel. In contrast, the macroeconomic variables, at least in their way of use in the predictive regression literature, emphasize the impact of only the realized values.

From the perspective of economic theory, Wachter (2006) shows that Campbell and Cochrane's (1999) habit-formation model can be adapted to explain the time-varying bond risk premia. Brandt and Wang (2003) argue that the bond risk premia are driven by inflation as well as by aggregate

[5]See Michael Aneiro, "Current yields", Barron's, M12, September 17, 2012. It is of interest to note that the market dropped further on the announcement day and the day after.

consumption. Bansal and Shaliastovich (2010) provide explanation on the predictability of bond risk premia based on long-run risks. However, there are no asset pricing models at present that can explain the intriguing forecasting ability of technical indicators on the bond risk premia. Our empirical findings call for new theories that incorporate technical variables into agents' information set as they do in practice, used widely by traders and investors.

The rest of the paper is organized as follows. Section 2 outlines the construction of technical indicators, as well as the estimation and evaluation of the in-sample and out-of-sample bond risk premia forecasts based on technical indicators. Section 3 reports the empirical results and Section 4 concludes.

2 Econometric Methodology

This section describes our econometric framework, which includes the construction of technical indicator, the estimation and evaluation of the in-sample and out-of-sample excess bond return forecast based on technical indicators.

2.1 Technical indicator construction

We follow Cochrane and Piazzesi (2005) for the notation of excess bond returns and yields. $p_t^{(n)}$ is the log price of n-year discount bond at time t. Then, the log yield of n-year discount bond at time t is $y_t^{(n)} \equiv -\frac{1}{n} p_t^{(n)}$. The n-year bond price at time t is $fs_t^{(n)} \equiv f_t^{(n)} - y_t^{(1)}$, where $f_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}$ is the forward rate at time t for loans between time $t+n-1$ and $t+n$. The excess log return on n-year discount bond from time t to $t+1$ is $rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$, where $r_{t+1}^{(n)} \equiv p_{t+1}^{(n-1)} - p_t^{(n)}$ is the log holding period return from buying an n-year bond at time t and selling it as an $n-1$ year bond at time $t+1$. The average excess log return across maturity is defined as $\overline{rx}_{t+1} \equiv \frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)}$.

Two groups of technical indicators are considered. The first one is an forward spread moving average trading rule MA^{fs} that generates a buy or sell signal ($S_t = 1$ or $S_t = 0$, respectively) at the end of period t by comparing two moving averages of n-year forward spreads:[6]

$$S_t = \begin{cases} 1 & \text{if} \quad MA_{s,t}^{fs,(n)} > MA_{l,t}^{fs,(n)} \\ 0 & \text{if} \quad MA_{s,t}^{fs,(n)} \leq MA_{l,t}^{fs,(n)} \end{cases}, \tag{1}$$

[6]Note that forward rate is the log-transformed bond price.

where

$$MA_{j,t}^{fs,(n)} = (1/j)\sum_{k=0}^{j-1} fs_{t-(k/12)}^{(n)} \qquad \text{for } j = s,l, \tag{2}$$

where $fs_{t-(k/12)}^{(n)}$ is the n-year forward spread at time $t-k/12$, and s (l) is the length of the short (long) forward spread moving average ($s < l$).[7] We denote the forward spread moving average rule with maturity n and lengths s and l as $MA^{fs,(n)}(s,l)$. Intuitively, the MA^{fs} rule is designed to detect the changes in trends of the bond prices.[8] For example, when the n-year forward rates have recently been falling relative to the one-year bond yields, the short forward spread moving average will tend to be lower than the long forward spread moving average and generating a sell signal. If the n-year forward rates begin trending upward relative to the one-year bond yields, then the short moving average tends to increase faster than the long moving average, eventually exceeding the long moving average and generating a buy signal. In Section 3, we analyze the monthly $MA^{fs,(n)}(s,l)$ rules with $n = 2,3,4,5$, $s = 3,6,9$ and $l = 18,24,30,36$.

Technical analysts frequently use volume data in conjunction with past prices to identify market trends. In light of this, the second type of technical indicator we consider employs "on-balance" stock market trading volume (e.g., Granville, 1963).[9] We first define

$$OBV_t = \sum_{k=1}^{12t} VOL_{k/12} D_{k/12}, \tag{3}$$

where $VOL_{k/12}$ is a measure of the stock market trading volume between period $(k-1)/12$ and $k/12$ and $D_{k/12}$ is a binary variable that takes a value of 1 if $P_{k/12} - P_{(k-1)/12} \geq 0$ and -1 otherwise. We then form a trading volume-based trading signal from OBV_t as

$$S_t = \begin{cases} 1 & \text{if} \quad MA_{s,t}^{OBV} \leq MA_{l,t}^{OBV} \\ 0 & \text{if} \quad MA_{s,t}^{OBV} > MA_{l,t}^{OBV} \end{cases}, \tag{4}$$

[7] The time indexation reflects the fact that, while the maturities of the Fama-Bliss discount bonds are from one year to five years, our data are sampled at a monthly frequency. Following Cochrane and Piazzesi (2005), we set the unit period to a year so that it matches the holding period of $rx_{t+1}^{(2)}, ..., rx_{t+1}^{(5)}$. The monthly sampling interval is then denoted as 1/12 of a year.

[8] Note that the forward rates move inversely with bond prices.

[9] We do not have bond trading volume data. We also experimented with testing the predictive power of technical indicators based on moving average of stock market index. Small predictive power for excess bond returns is detected in our sample. However, it becomes much less once controlling for economic predictors and our bond price moving average technical indicators. A potential explanation is that the forecasting information in the technical indicators based on stock price is captured by the stock market information contained in LN_t factor, particularly, the stock market factor, $\hat{F}_{8t}$, of LN_t that loads heavily on stock market index and dividend yield.

where

$$MA_{j,t}^{OBV} = (1/j) \sum_{k=0}^{j-1} OBV_{t-(k/12)} \qquad \text{for } j = s, l. \tag{5}$$

We denote the trading volume-based trading rule as $MA^{OBV}(s,l)$, where s (l) is the length of the short (long) moving average of "on-balance" trading volume ($s < l$). Intuitively, relatively high recent stock market volume together with recent stock price decrease indicates a strong negative stock market trend, and generates a buy signal for bond market. The stock market trading volume-based technical indicator might be related to "flight o quality" or "flight to liquidity" in view of high uncertainty and risk aversion, where bond returns tend to high relative to stock market returns and investors shift their portfolios from risky stock market towards safe short-term government bonds (Connolly, Stivers, and Sun, 2005; Caballero and Krishnamurthy, 2008; Beber, Brandt, and Kavajecz, 2009; Brunnermeier and Pedersen, 2009; Baele, Bekaert, and Inghelbrecht, 2010, among others). In Section 3, we compute monthly $MA^{OBV}(s,l)$ signals for $s = 1,2,3$ and $l = 9,12,15,18,21$.

The two types of technical indicators that we consider (bond price and trading volume-based) conveniently capture the trend-following idea at the center of technical analysis and are representative of the technical indicators analyzed in the academic literature (e.g., Brock, Lakonishok, and LeBaron, 1992; Sullivan, Timmermann, and White, 1999). In this paper, we seek to study whether technical indicators provide useful information for forecasting excess bond returns. Furthermore, we also aim to assess whether technical indicators could enhance excess bond return forecasts beyond that contained in the economic predictors. To investigate the latter question, we include Cochrane and Piazzesi (2005) forward rate factor CP_t and Ludvigson and Ng (2009) macroeconomic variable factor LN_t as control variables. Cochrane and Piazzesi (2005) find that the predictive power of a large number of financial indicators including forward rates and yields spreads is subsumed by their single forward-rate factor. Ludvigson and Ng (2009) find that their "real" and "inflation" factors have important predictive power for excess bond returns on U.S. government bonds beyond the predictive power contained in forward rates and yield spreads.

2.2 In-sample forecast

We use the standard predictive regression framework to analyze the in-sample predictive power of technical indictors for excess bond returns $rx_{t+1}^{(n)}$. However, analyzing the predictive power of a large number of potential technical predictors raises an important forecasting issue. Including all of the potential regressors simultaneously in a multiple regression model can produce a very good in-sample fit, but typically make in-sample over-fitting a significant concern, and thus most likely leads to very poor out-of-sample forecasting performance. To tractably incorporate information from all of the technical indicators while avoiding over-fitting, we, following Ludvigson and Ng (2007, 2009), use a principle component approach. Let $x_t = (x_{1,t}, ..., x_{N,t})'$ denotes the N-vector of potential technical predictors. Let $\hat{f}_t = (\hat{f}_{1,t}, ..., \hat{f}_{J,t})'$ represents the vector comprised of the first J principal components of x_t, where $J \ll N$. The number of common factors, J, is determined by the information criteria developed in Bai and Ng (2002). Intuitively, the principal components conveniently detect the key comovements in x_t, while filtering out much of the noise in individual technical predictors (e.g., Connor and Korajczyk, 1986, 1988; Ludvigson and Ng, 2007, 2009, 2011).

Since the pervasive factors in $\hat{f}_t$ may not be relevant in predicting excess bond returns $rx_{t+1}^{(n)}$, following Ludvigson and Ng (2009), we select the preferred set of technical analysis PC factor $\hat{F}_t$ from the different subsets of $\hat{f}_t$ using the Bayesian information criterion (BIC), which provides a way of selecting technical indicators factors with additional forecasting ability for excess bond returns among the factors in $\hat{f}_t$. Specifically, we first form different subsets of $\hat{f}_t$. We then regress $rx_{t+1}^{(n)}$ on this candidate subset and controlling economic predictors, and compute the corresponding BIC for each candidate subset of factors. The preferred set of technical indicators factors $\hat{F}_t$ is determined by minimizing the BIC.

We thus utilize the factor-augmented predictive regression to analyze the in-sample predictive power of technical indictor PC factor $\hat{F}_t$ for excess bond returns $rx_{t+1}^{(n)}$:

$$rx_{t+1}^{(n)} = \alpha' \hat{F}_t + \varepsilon_{t+1}, \qquad \text{for } n = 2, 3, 4, 5, \tag{6}$$

which analyzes the unconditional predictive power of technical indicators for excess bond returns. The null hypothesis is that $\alpha = 0$, and the technical indicators have no unconditional predictive ability for excess bond returns. The alternative hypothesis is that $\alpha \neq 0$, and the technical indicators are useful in predicting excess bond returns.

We are also interested in whether the technical indicators can be used in conjunction with economic predictors to further improve excess bond returns predictability from using economic predictors alone. To analyze the incremental predictive power of technical indicators, we include economic predictor Z_t in the regression model as conditioning variable:

$$rx_{t+1}^{(n)} = \alpha' \hat{F}_t + \beta' Z_t + \varepsilon_{t+1}, \qquad \text{for } n = 2,3,4,5, \tag{7}$$

where Z_t includes the Cochrane and Piazzesi (2005) forward rates factor CP_t and Ludvigson and Ng (2009) macroeconomic factor LN_t, which subsume the forecasting information in economic predictors including forward spreads, yield spreads, and a large number of macroeconomic variables. Thus (7) allows us to assess the incremental predictive power of technical indicators beyond economic predictors. Under the null hypothesis, α is equal to zero, and the technical indicators have no additional predictive power for excess bond returns once the economic predictors are included in regression model. Under the alternative hypothesis, α is different from zero, and the technical indicators are still useful in predicting excess bond returns even in presence of economic predictors.

In both (6) and (7), the standard errors of the regression coefficients are corrected for serial correlation using Newey and West (1987) with 18 lags, which is necessary since the annual log excess bond returns have an MA(12) error structure induced by overlapping observations. The Newey and West (1987) covariance matrix is positive definite in any sample, however, it underweights higher covariance. Following Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009), we use 18 lags to better ensure the correction for the MA(12) error structure.

2.3 Out-of-sample forecast

Although in-sample analysis may have more testing power, Goyal and Welch (2008), among others, argue that out-of-sample tests seem a more relevant standard for assessing genuine return predictability in real time in the context of stock market prediction. Therefore we also conduct analysis on the out-of-sample predictive ability of technical indicators for the excess bond returns. To avoid look-ahead bias and the use of future data, we generate out-of-sample forecasts of excess bond returns using recursive predictive regression, with all factors, including technical indicator factors $\tilde{F}_t$, forward rate factor CP_t, and macroeconomic factor LN_t, and parameters estimated just using information available up to the the month of forecast formation, t.[10]

First, we generate an out-of-sample forecast of excess bond return $rx_{t+1}^{(n)}$ based on out-of-sample

[10]Note that, while the technical indicator factor $\hat{F}_t$ used in the in-sample analysis is estimated using the full-sample information, the out-of-sample technical indicator factor $\tilde{F}_t$ is estimated using information available through the current time t.

technical indicator factor $\tilde{F}_t$, Equation (6), and information available through period t as

$$\widetilde{rx}_{t+1}^{(n)} = \tilde{\alpha}_t{}'\tilde{F}_t, \tag{8}$$

where $\tilde{\alpha}_t$ is a least squares estimate of α in (6) by regressing $\{rx_{(k/12)+1}^{(n)}\}_{k=1}^{12(t-1)}$ on $\{\tilde{F}_{k/12}\}_{k=1}^{12(t-1)}$. For each forecast formation period t, we first estimate the out-of-sample technical indicator PC factors $\{\tilde{f}_{k/12}\}_{k=1}^{12t}$ from a large number of potential individual technical indicators $\{x_{k/12}\}_{k=1}^{12t}$ using information available through period t. Then, the preferred subset of out-of-sample technical indicator factors $\{\tilde{F}_{k/12}\}_{k=1}^{12t}$ is selected from different subsets of $\{\tilde{f}_{k/12}\}_{k=1}^{12t}$ using the BIC criterion. Dividing the total sample of $12 \times T$ monthly observations into m first period sub-sample and q second period sub-sample, where $T = m/12 + q/12$, we can calculate a series of out-of-sample principle component forecasts of $rx_{t+1}^{(n)}$ based on $\tilde{F}_t$ over the last q monthly samples: $\{\widetilde{rx}_{k/12}^{(n)}\}_{k=m+1}^{12T}$.[11]

Second, to analyze whether including technical indicators with economic variables could further improve the out-of-sample forecasting gains for excess bond returns relative to either alone, we generate an out-of-sample forecast of excess bond return $rx_{t+1}^{(n)}$ based on both the technical indicator PC factor $\tilde{F}_t$ and the economic predictor Z_t, and information through forecast formation period t:

$$\widetilde{rx}_{t+1}^{(n)} = \tilde{\alpha}_t{}'\tilde{F}_t + \tilde{\beta}_t{}'Z_t, \tag{9}$$

where Z_t includes the Cochrane and Piazzesi (2005) forward rates factor CP_t or Ludvigson and Ng (2009) macroeconomic factor LN_t. $\tilde{\alpha}_t$ and $\tilde{\beta}_t$ are least squares estimates of α and β in (7) from regressing $\{rx_{(k/12)+1}^{(n)}\}_{k=1}^{12(t-1)}$ on $\{\tilde{F}_{k/12}\}_{k=1}^{12(t-1)}$ and $\{Z_{k/12}\}_{k=1}^{12(t-1)}$, respectively. We then can compute a series of conditional out-of-sample excess bond return forecasts based on $\tilde{F}_t$ and Z_t over the last q monthly out-of-sample evaluation samples: $\{\widetilde{rx}_{k/12}^{(n)}\}_{k=m+1}^{12T}$. In addition, to assess the incremental forecasting power of technical indicators over economic variables, we also generate out-of-sample forecasts utilizing the information in economic predictor Z_t alone:

$$\widetilde{rx}_{t+1}^{(n),R} = \tilde{\beta}_t{}'Z_t, \tag{10}$$

where $\tilde{\beta}_t$ is a least squares slope coefficient estimate based on information available through t.

[11]Observe that the forecasts are generated using a recursive (i.e., expanding) window for estimating α_t and β_t in (8). Forecasts could also be generated using a rolling window (which drops earlier observations as additional observations become available) in recognition of potential structural instability. Pesaran and Timmermann (2007) and Clark and McCracken (2009), however, show that the optimal estimation window for a quadratic loss function can include prebreak data due to the familiar bias-efficiency tradeoff. We use recursive estimation windows in Section (3.3), although we obtain similar results using rolling estimation windows of various sizes.

The historical average of excess bond returns, $\overline{rx}^{(n)}_{t+1} = \frac{1}{12t}\sum_{k=1}^{12t} rx^{(n)}_{k/12}$, is the natural forecast benchmark for (8), (9), and (10) corresponding to the the constant expected excess return model ($\alpha = 0$ in (6) and (7)). Goyal and Welch (2008) show that historical average forecast is a stringent benchmark in stock market, and forecasts based on economic variables frequently fail to outperform the historical average forecast in out-of-sample.

We use two metrics for evaluating the out-of-sample bond risk premia forecasts based on technical indicators or economic variables. The first is the Campbell and Thompson (2008) R^2_{OS} statistic, which measures the reduction in mean square prediction error (MSPE) for a competing predictive regression model which includes technical indicators or economic variables relative to the historical average forecast benchmark,

$$R^2_{OS} = 1 - \frac{\sum_{k=m+1}^{12T}(rx^{(n)}_{k/12} - \widetilde{rx}^{(n)}_{k/12})^2}{\sum_{k=m+1}^{12T}(rx^{(n)}_{k/12} - \overline{rx}^{(n)}_{k/12})^2}, \tag{11}$$

where $rx^{(n)}_{k/12}$ represents the excess log return on n-year government bond from time $k/12-1$ to $k/12$, $\widetilde{rx}^{(n)}_{k/12}$ represents a competing out-of-sample forecast for $rx^{(n)}_{k/12}$ based on technical indicators or economic variables, and $\overline{rx}^{(n)}_{k/12}$ represents the historical average benchmark. Thus, when $R^2_{OS} > 0$, the competing forecast outperforms the historical average benchmark in term of MSPE. We employ the Clark and West (2007) *MSPE-adjusted* statistic to test the null hypothesis that the competing model MSPE is greater than or equal to the restricted predictive benchmark MSPE, against the one-sided alternative hypothesis that the competing forecast has lower MSPE, corresponding to H_0: $R^2_{OS} \leq 0$ against H_A : $R^2_{OS} > 0$.[12] Clark and West (2007) develop the *MSPE-adjusted* statistic by modifying the familiar Diebold and Mariano (1995) and West (1996) statistic so that it has a standard normal asymptotic distribution when comparing forecasts from nested models.[13] Comparing the competing predictive regression forecast with the historical average benchmark entails comparing nested models.

R^2 statistics are typically large for bond risk premia forecasts, but a relatively large R^2 may imply little economic significance for an investor (e.g., Della Corte, Sarno, and Thornton 2008;

[12]The standard error in *MSPE-adjusted* statistic is adjusted for serial correlation using Newey and West (1987) with 18 lags.

[13]While the Diebold and Mariano (1995) and West (1996) statistic has a standard normal asymptotic distribution when comparing forecasts from non-nested models, Clark and McCracken (2001) and McCracken (2007) show that it has a complicated non-standard distribution when comparing forecasts from nested models. The non-standard distribution can lead the Diebold and Mariano (1995) and West (1996) statistic to be severely undersized when comparing forecasts from nested models, thereby substantially reducing power.

Thornton and Valente, 2012). From an asset allocation perspective, however, utility gain itself is the key economic metric. As a second metric for evaluating out-of-sample excess bond return forecasts, we thus compute utility gains for a mean-variance investor who optimally allocates across n-year Treasury bond $rx_{t+1}^{(n)}$ and and 1-year risk-free bill, as in, among others, Kandel and Stambaugh (1996), Marquering and Verbeek (2004), Campbell and Thompson (2008), Della Corte, Sarno, and Thornton (2008), Neely, Rapach, Tu and Zhou (2011), and Thornton and Valente (2012). As discussed in the introduction, this procedure addresses the weakness of many existing studies of technical indicators that fail to incorporate the degree of risk aversion into the asset allocation decision.

In particular, we compute the average utility for a mean-variance investor with risk aversion coefficient of three who monthly allocates between n-year Treasury bond and 1-year risk-free bill using an out-of-sample excess bond return forecast generated by a competing forecast model including technical indicators or economic variables as predictors versus a historical average forecast benchmark corresponding to the constant expected excess bond return model. At the end of period t, the investor allocates

$$w_{t+1}^{(n)} = \frac{1}{\gamma} \frac{\widetilde{rx}_{t+1}^{(n)}}{\tilde{\sigma}_{t+1}^{(n),2}} \tag{12}$$

of his wealth to n-year Treasury bond during period $t+1$, where γ is the coefficient of risk aversion, $\widetilde{rx}_{t+1}^{(n)}$ is a competing out-of-sample forecast for excess n-year bond return based on technical indicators or economic variables, and $\tilde{\sigma}_{t+1}^{(n),2}$ is a forecast of the excess n-year bond return variance. We assume that the investor uses a four-year moving window of past excess bond returns to estimate the variance (e.g., Campbell and Thompson, 2008). Following Thornton and Valente (2012), we constrain the portfolio weight on n-year bond to lie between -1 and 2 to prevent extreme investments and limit the impact of estimation error.[14] The average utility for the investor who incorporates information contained in technical indictors or economic variables into the predictive model of excess n-year bond return is given by

$$\hat{v}^{(n)} = \hat{\mu}^{(n)} - 0.5\gamma\hat{\sigma}^{(n),2}, \tag{13}$$

where $\hat{\mu}^{(n)}$ and $\hat{\sigma}^{(n),2}$ are the sample mean and variance, respectively, for the the portfolio formed on Equation (12) using the sequence of forecasts $\widetilde{rx}_{t+1}^{(n)}$ over the last q out-of-sample evaluation

[14]Our results are robust to alternative portfolio weight constraints. Utility gains could be even larger when moderately relaxing the portfolio weight constraints.

samples.

We then calculate the average utility for the same investor who instead uses the historical average forecast to predict the excess n-year bond return. At the end of period t, the investor allocates

$$w_{t+1}^{(n),R} = \frac{1}{\gamma} \frac{\overline{rx}_{t+1}^{(n)}}{\tilde{\sigma}_{t+1}^{(n),2}} \tag{14}$$

to n-year Treasury bond during period $t+1$, where $\overline{rx}_{t+1}^{(n)}$ is the historical average forecast for $rx_{t+1}^{(n)}$. The investor then realizes an average utility of

$$\bar{v}^{(n)} = \bar{\mu}_R^{(n)} - 0.5\gamma\bar{\sigma}_R^{(n),2}, \tag{15}$$

during the out-of-sample evaluation period, where $\bar{\mu}_R^{(n)}$ and $\bar{\sigma}_R^{(n),2}$ are the sample mean and variance, respectively, for the the portfolio formed on Equation (14) using the sequence of historical average forecast $\overline{rx}_{t+1}^{(n)}$. The utility gain is the difference between (13) and (15), $\hat{v}^{(n)} - \bar{v}^{(n)}$, which can be interpreted as the annual percentage portfolio management fee that an investor would be willing to pay to have access to the bond risk premium forecast $\widetilde{rx}_{t+1}^{(n)}$ using technical indicators or economic variables relative to the historical average benchmark $\overline{rx}_{t+1}^{(n)}$ corresponding to the constant expected excess bond return model (no predictability).

3 Empirical Results

This section describes the data, and reports the in-sample test results and out-of-sample results for the R_{OS}^2 statistics and average utility gains regarding forecasting excess bond returns using technical indicators.

3.1 Data

Our monthly data span 1964:01−2007:12.[15] The short-term zero coupon U.S. Treasury bond prices with maturities from one- through five-years are from Fama-Bliss dataset available from the Center for Research in Securities Prices (CRSP). We obtain the long-term U.S. Treasury bond data with maturities from seventeen- to twenty-years from the Federal Reserve's website, which

[15]Due to data restrictions, we currently only have the data up to 2007:12.

provides updated data from Gürkaynak, Sack, and Wright (2007) beginning in 1981:06.[16] We compute the yields, forward rates, forward spreads, and annual excess bond returns at a monthly frequency as described in Section (2.1). The macroeconomic fundamentals data used in Ludvigson and Ng (2009, 2011) are from Sydney C. Ludvigson's web page.[17] We use the monthly forward spreads when computing the forward spread moving average technical indicators as in Equation (1). In addition, we use monthly S&P 500 index and stock market trading volume data from Google Finance to compute the trading volume-based trading signals in Equation (4).

Table 1 reports summary statistics for our forward spread moving average technical indicator PC factors, $\hat{f}_t^{fs}$, and trading volume technical indicator PC factors, $\hat{f}_t^{OBV}$, which are estimated from 48 forward spread moving average technical indicators and 15 trading volume technical indicators, respectively.[18] $\hat{f}_t^{fs}$ and $\hat{f}_t^{OBV}$ contain five and three PC factors, respectively. The number of factors is determined using the information criterion developed by Bai and Ng (2002). These technical PC factors during period t are estimated using full sample of time-series information from 1964:01 to 2007:12. These in-sample PC factors are used to test the in-sample predictive power of technical indicators in Section (3.2). We also conduct analysis on the out-of-sample predictive power of the technical indicators in Sections (3.3) and (3.4), in which the out-of-sample PC factors $\tilde{f}_t^{fs}$ and $\tilde{f}_t^{OBV}$ are estimated recursively using data only available to forecast formation period t, as described in Section (2.3).

Column R_i^2 of Table 1 shows that a small number of technical PC factors describe a large fraction of the total variation in the data.[19] R_i^2 measures the relative importance of the ith PC factor, which is calculated as the fraction of total variance in those technical indicators explained by factors 1 to i.[20] Column R_i^2 of Table 1, Panel $\hat{f}_{i,t}^{fs}$ shows that the first PC factor accounts for around 70% of the total variation in the 48 MA^{fs} technical indicators based on forward spread moving averages, and the first three and five PC factors further increase the R_i^2 to around 80%

[16]The Gürkaynak, Sack, and Wright (2006) dataset is available at http://www.federalreserve.gov/pubs/feds/2006. Note that the differences between Gürkaynak, Sack, and Wright (2006) and Fama-Bliss dataset are quite small on most dates (e.g., Cochrane and Piazzesi, 2008).

[17]The data are available at http://www.econ.nyu.edu/user/ludvigsons/Data&ReplicationFiles.zip

[18]An alternative set of technical PC factors can be estimated on the panel of 63 technical trading rules (pooling the MA^{fs} rules and MA^{OBV} rules together). However, we do not report the results for this method since the results are similar. In addition, the factors estimates from this method are often criticized for being difficult to interpret. Grouping data into two groups based on trading rules to be moving-average or trading volume permits us to easily name and interpret the factors.

[19]The first factor explains the largest fraction of the total variation in those technical indicators, where the total variation is defined as the sum of the variance of the individual technical indicators. And the ith factor explains the ith largest fraction of the total variation. The PC factors are mutually orthogonal.

[20]R_i^2 is calculated by dividing the sum of the first i largest eigenvalues of the matrix xx', the sample covariance matrix of the technical indicators, to the sum of all eigenvalues.

and 85%, respectively. Column R_i^2 of Table 1, Panel $\hat{f}_{i,t}^{OBV}$ presents that the first PC factor alone explains up to 80% of the total variation in the 15 MA^{OBV} technical indicators based on trading volume, and the first three PC factors describe around 95% of the total variation.

Column $AR1_i$ of Table 1 displays the first-order autoregressive coefficients of AR(1) model for each factor. Significant difference in persistence are found among PC factors. The autoregressive coefficients for forward spread moving average technical factors $\hat{f}_t^{fs}$ are in the range of 0.82–0.97, and trading volume-based technical factors $\hat{f}_t^{OBV}$ have autoregressive coefficients range of 0.00 to 0.92.[21]

We determine the preferred subset of technical indicator factors $\hat{\mathbf{F}}_t^{TI}$ from all of the possible combinations of the estimated technical PC factors using the short-term government bonds and BIC criterion. With Cochrane and Piazzesi (2005) factor CP_t and Ludvigson and Ng (2009) factor LN_t included as conditioning variables, three technical indicator factors, $\hat{\mathbf{F}}_t^{TI} = (\hat{\mathbf{F}}_t^{fs}, \hat{\mathbf{F}}_t^{OBV}) = (\hat{F}_{1,t}^{fs}, \hat{F}_{3,t}^{fs}, \hat{F}_{1,t}^{OBV})$, are selected based on full sample information spanning the period 1964:01−2007:12, where two-factor subset $\hat{\mathbf{F}}_t^{fs} = (\hat{F}_{1,t}^{fs}, \hat{F}_{3,t}^{fs}) \subset \hat{f}_t^{fs}$ and one-factor subset $\hat{\mathbf{F}}_t^{OBV} = \hat{F}_{1,t}^{OBV} \subset \hat{f}_t^{OBV}$. Note that the out-of-sample factors $\tilde{\mathbf{F}}_t^{fs}$, $\tilde{\mathbf{F}}_{t,t}^{OBV}$, and $\tilde{\mathbf{F}}_{t,t}^{TI}$ in Sections (3.3) and (3.4) are determined recursively using data only available through forecast formation period t, as described in Section (2.3).

3.2 In-sample analysis

Table 2 reports regression slope coefficients, heteroskedasticity and serial correlation robust t-statistics, and adjusted R^2 for in-sample predictive regression of log excess returns of short-term n-year government bonds, $rx_{t+1}^{(n)}$, with $n = 2,...,5$ on lagged technical indicator factors over the full sample period 1964:01−2007:12.[22] Following Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009), the standard error of the regression coefficient is corrected for serial correlation using Newey and West (1987) with 18 lags, since the annual log excess bond returns have an MA(12) error structure induced by overlapping observations. (6) and (7) examine separately the in-sample predictability of technical indicator factors for excess bond returns either excluding or including economic predictors, and the results are reported in rows 1–3 and 4–6, respectively. To test the incremental predictive power of technical factors beyond that contained in the economic variables, CP_t and LN_t, the Cochrane and Piazzesi (2005) factor and Ludvigson and Ng (2009)

[21]The relatively high persistence of technical indicators factors are consistent with trend following idea of technical analysis, that are designed to detect the trending patterns in the market.

[22]We find similar results for raw excess returns.

factor, respectively, are included in Z_t of (7) as conditioning variables. The in-sample forecasting results of using CP_t or LN_t alone are reported in rows 7–9 as benchmark forecasts.

As benchmark forecasts, Rows 7–9 of the top panel of Table 2 report the in-sample predictive regression results of CP_t and LN_t for two-year excess bond returns $rx_{t+1}^{(2)}$. As shown in Row 8, consistent with the Cochrane and Piazzesi (2005), the forward rate factor CP_t alone generates huge adjusted R^2 of 31% for two-year excess bond returns. Row 9 presents that the macroeconomic variable factor LN_t alone has sizable R^2 of 23% too. Similar to the results reported in Ludvigson and Ng (2009), combining information from CP_t and LN_t together further improves R^2 to 45%.

Rows 1 to 3 of the top panel of Table 2 show the in-sample forecasting results for two-year excess bond returns $rx_{t+1}^{(2)}$ based on technical indicator factors alone. The forward spread moving average technical indicator factor $\hat{\mathbf{F}}_t^{fs}$ has significant predictive power for $rx_{t+1}^{(2)}$ as shown in Row 1. And the selected two-factor subset $\hat{F}_{1,t}^{fs}$ and $\hat{F}_{3,t}^{fs}$, which are the first and third PC factors estimated from 48 forward spread moving average trading signals, explain 28% of the two-year excess bond return variation, with statistical significance at the 1% or better level. According to Row 2, the trading volume technical indicator factor $\hat{\mathbf{F}}_t^{OBV}$ also is a significant predictor for $rx_{t+1}^{(2)}$. The one-factor subset $\hat{F}_{1,t}^{OBV}$, the first PC factor estimated from 15 trading volume technical indicators, is statistically significant at the 5% level, and generates adjusted R^2 of 10%. In addition, Row 3 shows that $\hat{\mathbf{F}}_t^{TI}$ which includes information from forward spread moving average and trading volume-based technical indicators together outperforms either alone and produces highest R^2 of 32%, with all factors statistically significant at the conventional level. Following Ludvigson and Ng (2009), we inspect the relative importance of the three technical indicator factors in $\hat{\mathbf{F}}_t^{TI}$ using absolute value of regression coefficients, and find that all of the three technical factors have economically large value. Therefore, technical indicators contain significant forecasting power for two-year excess bond returns of about the same economic scale with economic variables CP_t and LN_t in term of R^2, and both the forward spread moving average and trading volume-based technical indicators are useful.

We turn next to examine whether the technical indicators have incremental predictive power for two-year excess bond returns beyond that contained in economic variables CP_t and LN_t. Rows 4 through 6 of the panel $rx_{t+1}^{(2)}$ in Table 2 show that technical indicator factors have significant predictive power even in the presence of CP_t and LN_t. All the technical factors are statistically significant at reasonable level. Moreover, the forecasts utilizing information in both technical indicators and economic variables generate sizable adjusted R^2 of 47%, and outperform the corresponding forecasts based on economic variables or technical indicators alone, suggesting that technical indicators contain additional forecasting information beyond that contained in forward rates, yields, and macroeconomic variables.[23]

The remaining three panels of Table 2 show that technical indicator factors also have strong in-sample forecasting power for excess returns of shot-term government bonds with maturities of three, four, and five years. Both the forward spread moving average and trading volume-based technical indicators predict excess bond returns of all maturities significantly, with adjusted R^2 up to 35%. Moreover, The technical indicators have significant predictive power for excess bond returns of each short-term government bond even in presence of economic predictors CP_t and LN_t. For example, adding the technical indicator factor $\hat{\mathbf{F}}_t^{TI}$ to CP_t and LN_t increases the R^2 from 40% to 44% for the five-year excess bond returns. In summary, both the technical indicators and economic variables contain significant forecasting information for excess returns of short-term government bonds, and technical indicators and economic variables should be utilized together in forecasting short-term government bonds.

As discussed before, most of the current literature on bond risk premia predictability focus on short-term government bonds with maturities of 2–5 years. Complimenting to the earlier papers like Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009), Table 3 studies the in-sample predictability of excess returns of long-term government bonds with maturities ranging from 17 to 20 years over the sample period from 1981:06 to 2007:12 due to data availability.

Row 8 of Table 3 shows that forward rate factor CP_t generates sizable R^2 of 27–28% for excess returns on long-term government bonds, so CP_t contains large in-sample forecasting power for both short-term and long-term government bonds. Strikingly, According to Row 9 of Table 3, the in-sample R^2 of macroeconomic variable factor LN_t diminishes sharply to about 5% for seventeen- to twenty-year government bonds, significantly smaller than the corresponding 14–23% R^2 range for two- to five-year short-term government bonds in Table 2, suggesting that LN_t alone has little forecasting power for long-term government bonds.

However, the technical indicators factor $\hat{\mathbf{F}}_t^{TI}$ selected to best predict the short-term bond risk premium, has much higher R^2 for excess returns on long-term government bonds than the corresponding R^2 for short-term government bonds in Table 2, about a value of 45% for all the long-term maturities (see Row 3 of Table 3). Moreover, the in-sample R^2s of utilizing technical indicators

[23] Following Cochrane and Piazzesi (2005), we find that a single-factor predictor which is a single linear combination of the selected three technical indicator factors has almost the same predictive power as do the competing models that include the three technical factors contained in $\hat{\mathbf{F}}_t^{TI}$ as separate predictors.

alone to predict long-term bond risk premia are substantially larger than the R^2s of utilizing economic variables CP_t and LN_t alone, indicating that technical indicators play a bigger role in predicting excess returns on long-term government bonds comparing to economic variables. Again, when utilizing information from both technical indicators and economic variables together, the forecasts perform the best in predicting excess long-term bond returns, with R^2 in the range of 46–47%. Among the three technical indicator factors, $\hat{F}^{fs}_{1,t}$ and $\hat{F}^{fs}_{3,t}$, the two forward spread technical indicator factors belonging to subset $\hat{\mathbf{F}}^{fs}_t$, are particularly useful, which have economically large absolute regression coefficients, and are statistically significant at about 1% level for all the long-term government bonds.[24]

3.3 R^2_{OS} statistics

Panel A of Table 4 reports the Campbell and Thompson (2008) R^2_{OS} statistics for out-of-sample excess bond return forecasts of short-term n-year Treasury bonds with maturities from two to five years based on Cochrane and Piazzesi (2005) forward rates factor CP_t, Ludvigson and Ng (2009) macroeconomic factor LN_t, and forward spread moving average technical indicator factors $\tilde{\mathbf{F}}^{fs}_t$ relative to the historical average benchmark forecast over the 1975:01–2007:12 out-of-sample forecast evaluation period. We use the 1964:01 − 1974:01 as the initial in-sample period when forming the recursive out-of-sample forecasts of 1975:01. $\tilde{\mathbf{F}}^{fs}_t$ is selected to best predict the short-term government bonds recursively from PC factors estimated from 48 forward spread moving average technical indicators MA^{fs} according to the BIC criterion. All the predictors and parameters are estimated recursively using only the information available through forecast formation period t. Forming forecasts in this manner simulates the situation of an investor in real time. We assess the statistical significance of R^2_{OS} using the Clark and West (2007) *MSPE-adjusted* statistic, as described in Section 2.3.

The third column of Table 4, Panel A shows that Cochrane and Piazzesi (2005) forward rates factor CP_t alone has positive R^2_{OS} statistics relative to the historical average for excess returns on short-term government bonds with maturities ranging from 2 to 5 years. As is the case for stock market, the R^2_{OS} statistics are generally smaller than the in-sample ones. But all of the R^2_{OS} are still economically sizable, in the range of 15.2–17.9%, and all of which are statistically significant at 5% level. In contrast, the fifth column of Panel A shows that the R^2_{OS} of Ludvigson and Ng

[24]Note that our forward spread technical indicators are based on short-term bond prices due to data availability. However, adding technical indicators based on long-term bond prices generates the similar results in predicting long-term bond risk premia.

(2009) macroeconomic factor LN_t are 4.7%, 0.1%, -1.4%, and -4.2%, respectively, sharply smaller than the in-sample ones. Two of four R^2_{OS} are positive, and only the one for two-year bond is economically large (4.7%) and statistically significance at 5% level. In addition, according to in the seventh column of Panel A, all of four forecasts based on CP_t and LN_t together are economically sizable with statistical significance at 5% level or better, and two-year bond has the highest R^2_{OS} of 19.4%.

Turing to the results for $\tilde{\mathbf{F}}^{fs}_t$, the forward spread moving average technical indicator factor, in Panel A of Table 4, the results in the second column of Panel A shows that $\tilde{\mathbf{F}}^{fs}_t$ alone produce large positive R^2_{OS} statistics for excess bond returns of two- to five-year bonds. The R^2_{OS} are in the range of 22.9–25.2%, and all of which are significant at 1% or better level. Thus forward spread technical indicators have economically and statistically significant out-of-sample predictive power for excess bond returns relative to the historical average benchmark in term of MSPE, and at least as useful as economic variables. In addition, maturities seems to enhance the out-of-sample forecasting power of $\tilde{\mathbf{F}}^{fs}_t$, and R^2_{OS} of $\tilde{\mathbf{F}}^{fs}_t$ improve monotonically from 22.9% to 25.2%, as bond maturities increasing from two years to five years.

Neely, Rapach, Tu and Zhou (2011) show that equity risk premium forecasts utilizing information from both technical indicators and economic variables substantially improve the forecasting performance relative to either alone. We illustrate the out-of-sample gains of excess bond return forecasts employing economic variables CP_t and LN_t and forward spread technical indicators factor $\tilde{\mathbf{F}}^{fs}_t$ together in the remaining columns of Table 4, Panel A. The fourth column of Panel A reveals that the R^2_{OS} statistics of using CP_t and $\tilde{\mathbf{F}}^{fs}_t$ in conjunction range from 25.5% to 27.7% relative to the historical average forecast, all of which are statistically significant at 1% level and well above all of the corresponding R^2_{OS} of the forecasts based on CP_t or $\tilde{\mathbf{F}}^{fs}_t$ alone in the third and second columns of Panel A. According to the sixth column of Panel A, all of the four R^2_{OS} statistics using LN_t and $\tilde{\mathbf{F}}^{fs}_t$ together are statistically and economically significant, markedly larger than all of the corresponding R^2_{OS} for the forecasts based on LN_t or $\tilde{\mathbf{F}}^{fs}_t$ alone in the fifth and second columns of Panel A, respectively. In addition, the eighth column of Panel A show that utilizing CP_t, LN_t, and $\tilde{\mathbf{F}}^{fs}_t$ together further enhance R^2_{OS} to about 29%. In summary, these results indicate that forward spread technical indicators factor $\tilde{\mathbf{F}}^{fs}_t$ contains complementary forecasting information beyond that contained in economic variables like CP_t and LN_t, and using $\tilde{\mathbf{F}}^{fs}_t$ and economic variables together improves the out-of-sample forecasting performance for short-term Treasury bonds.

The Panel B of Table 4 presents the R^2_{OS} statistics of $\tilde{\mathbf{F}}^{OBV}_t$, the trading volume technical indicator factor. The second column of Panel B shows that $\tilde{\mathbf{F}}_t^{OBV}$ alone produce consistently positive R^2_{OS} statistics for short-term government bonds ranging from 5.1% to 7.9% with statistical significance at 1% level. And two-year bond is most predictable by $\tilde{\mathbf{F}}_t^{OBV}$ with R^2_{OS} of 7.9%. The fourth column of Table 4, Panel B presents that utilizing CP_t and $\tilde{\mathbf{F}}_t^{OBV}$ together generates large positive R^2_{OS} across all of the four short-term bonds, and consistently outperform that of CP_t and $\tilde{\mathbf{F}}_t^{OBV}$ alone. According to the sixth column of Panel B, all of the four R^2_{OS} statistics using LN_t and $\tilde{\mathbf{F}}_t^{fs}$ together are larger than the corresponding R^2_{OS} based on LN_t alone, all of four R^2_{OS} are positive and statistically significant at reasonable level. Moreover, the eighth column of Panel B shows that, adding $\tilde{\mathbf{F}}_t^{fs}$ with CP_t and LN_t consistently beat the forecasts with CP_t and LN_t together and further enhance the R^2_{OS} to the range of 18.1–24.1%. Therefore trading volume technical indicators produce significant forecasting power for short-term Treasury bonds.

Panel C of Table 4 reports results for forecasts based on technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ based on both the forward spread-based and trading volume-based technical indicators. The R^2_{OS} statistics of $\tilde{\mathbf{F}}_t^{TI}$ in the second column of Panel C are about 26%, all of the four are economically large and statistically significant at 1% level, and outperform the corresponding forecasts based on $\tilde{\mathbf{F}}_t^{fs}$ or $\tilde{\mathbf{F}}_t^{OBV}$ alone in Panel A and B, respectively, signalling the relevance of both the forward spread and trading volume-based technical indicators in forecasting bond risk premia. The fourth column of Panel C indicate that the R^2_{OS} based $\tilde{\mathbf{F}}_t^{TI}$ and CP_t together are about 30%, all of which are above the corresponding R^2_{OS} of $\tilde{\mathbf{F}}_t^{TI}$ or CP_t alone. The sixth column of Panel C shows that all of four R^2_{OS} based $\tilde{\mathbf{F}}_t^{TI}$ and LN_t together are above that of either alone too, with the sizable R^2_{OS} up to 29.8%. In addition, the eighth column of Panel C shows that, forecasts based on $\tilde{\mathbf{F}}_t^{TI}$, CP_t and LN_t together perform the best and further improve the R^2_{OS} for short-term government bonds to the range of 30.7–33.2%.

Table 5 reports the R^2_{OS} statistics for excess returns of two- to five-year Treasury bonds over 1985:01−2007:12 out-of-sample evaluation periods. The third and fifth columns of Panel A shows that both CP_t and LN_t produce sizable positive R^2_{OS} for two- to five-year bonds, with the R^2_{OS} up to 28.9% and 11.4%, respectively, and all of which are statistically significant at reasonable level. Forecasts based on CP_t and LN_t in conjunction generates even bigger R^2_{OS} up to 34%, well beyond that of CP_t and LN_t alone. According to second column of Table 5, although there are some variation across time, technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ and its two constituting components $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ consistently produce large positive forecasting gains relative to historical average for short-term Treasury bonds. For example, $\tilde{\mathbf{F}}_t^{TI}$ delivers sizable R^2_{OS} range of 22.3–29.6%, which are comparable to that of economic variables CP_t and LN_t. Moreover, the fourth, sixth, and eighth columns of Table 5 indicate that forecasts employing both economic variables and technical indicators together substantially improve over that based on either alone. For example, using $\tilde{\mathbf{F}}_t^{TI}$ together with CP_t and LN_t generates sizable forecasting gain up to 43% in the last column of Panel C.

Table 6 turns to examine the out-of-sample predictability of excess returns on long-term government bonds with maturities from 17 to 20 years over 1985:01−2007:12 out-of-sample evaluation periods, alone with the historical average benchmark. Data availability limits the starting date for the seventeen- to twenty-year bond prices to 1981:07, thus we use the 1981:06−1984:01 as the initial in-sample period to estimate the predictive regression models. The third column of Panel A, Table 6 shows that Cochrane and Piazzesi (2005) forward rates factor CP_t produce sizable positive R^2_{OS} about 24% for all the long-term government bonds, all of which are statistically significant at 1% level. Thus CP_t has consistent forecasting power for both short- and long-term government bonds relative to historical average in term of MSPE. However, the fifth column shows that Ludvigson and Ng (2009) macroeconomic factor LN_t has poor forecasting performance for long-term government bonds,[25] and all of the R^2_{OS} statistics are negative with large absolute value, indicating the historical average outperforms LN_t in forecasting long-term Treasury bonds.

The second column of Table 6, Panel A indicates that $\tilde{\mathbf{F}}_t^{fs}$, the forwards spread moving average technical indicator factor, substantially outperforms the historical average benchmark forecast for seventeen- to twenty-year bonds, with R^2_{OS} range of 39.4% to 44.0%, much larger than the 25.6–33.9% range for short-term government bonds over the same out-of-sample evaluation period in Table 5. Therefore, consistent with the previous in-sample results, $\tilde{\mathbf{F}}_t^{fs}$ has higher out-of-sample forecasting power for long-term government bonds than for short-term government bonds in term of R^2_{OS}. Moreover, forecasts including $\tilde{\mathbf{F}}_t^{fs}$ together with economic variables CP_t and LN_t substantially outperform the historical average and corresponding conventional forecasts based on CP_t and LN_t alone (see the fourth, sixth, and eighth columns of Table 6, Panel A). For example, according to the sixth column of Panel A, in contrast to the poor performance of the forecasts based on LN_t alone in the fifth column of Table 6, all of the four R^2_{OS} of forecasts based on $\tilde{\mathbf{F}}_t^{fs}$ and LN_t together are sizable positive, ranging from 28.2% to 33.8% for seventeen- to twenty-year bonds. Despite the positive forecasting gains of $\tilde{\mathbf{F}}_t^{OBV}$ for short-term government bonds, it fails to beat the historical average in predicting excess long-term government bond returns (see Panel B of Table 6). However, the second column of Panel C of Table 6 shows that $\tilde{\mathbf{F}}_t^{TI}$, which utilizes information

[25]The Ludvigson and Ng (2009) macroeconomic factors for long-term bonds are determined recursively based on the information available through period of forecast formation t according to the BIC criterion.

in both forward spread-based and trading volume-based technical indicators, consistently deliver large positive forecasting gains up to 21% for long-term government bonds. Moreover, when combining information from all of the economic variables and technical indicators together, the R^2_{OS} are in the range of 20.1–24.4%, which is economically sizable and statistically significant although smaller than that for short-term government bonds in Table 4 and 5.

3.4 Asset Allocation

Table 7 reports the out-of-sample asset allocation results for a mean-variance investor with risk aversion coefficient of three who optimally allocates a portfolio between one-year risk-free Treasury bill and n-year Treasury bond using the competing bond risk premia forecasts generated from some or all of the economic variables CP_t and LN_t and technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$. Panels A and B report the average utility gains, in annualized percent, for the portfolios constructed on short-term government bonds with maturities n of 2–5 years over 1975:01−2007:12 and 1985:01−2007:12 out-of-sample evaluation periods, respectively, and Panel C reports the average utility gains for the portfolios constructed on long-term government bonds with maturities n of 17–20 years over 1985:01−2007:12 evaluation period. The average utility gain is the portfolio management fee (in annualized percent return) that an investor would be willing to pay to have access to the competing bond risk premia forecast vis-á-vis the historical average forecast benchmark which ignores the predictability in bond risk premia.

The third column of Panel A, Table 7 shows that, as reported by Thornton and Valente (2012) among others, forecasts based on CP_t generate very limited economic value for short-term government bonds over 1975:01−2007:12 out-of-sample evaluation period. Two of four utility gains are positive, and only the one on five-year bond is economically meaningful of 0.70%. The fifth column of Panel A, Table 7 further shows that macroeconomic factor LN_t has little value for short-term government bonds too, with the utility gains ranging from −0.89% to −0.53%. Thus a simple portfolio strategy based on historical average outperforms the timing portfolio according to forecasts based on LN_t over 1975:01−2007:12 period in the view of economic value. However, the economic value of CP_t and LN_t for short-term government bonds is markedly improved over the more recent 1985:01−2007:12 period as shown in the third and fifth columns of Table 8, ranging from 0.32% to 3.07% and from −0.07% to 0.73% for CP_t and LN_t, respectively. So the investor will be willing to pay annual management fee more than 3% and 0.7% to have access to the forecasts generated from CP_t and LN_t, respectively, over 1985:01−2007:12 evaluation period.

In summary, the results in Panels A and B suggest that the bond risk premia forecasts based on economic variables CP_t and LN_t at least fail to generate consistent economic value over time in out-of-sample despite of huge R^2_{OS} in Tables 4 and 5.

The second column of Panels A and B, Table 7 demonstrates that the utility gains of technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ for short-term government bonds are substantially higher and more consistent over time. All of the eight utility gains are large positive, in the range of 1.04–2.06% and 1.08–4.02% over 1975:01−2007:12 and 1985:01−2007:12 evaluation periods, respectively, with the five-year bond return forecasts generating the largest utility gains. The remaining columns provide further evidences that adding technical indicators with CP_t or LN_t consistently and substantially improves over the forecasts based on CP_t or LN_t alone in term of utility gain. Comparing the seventh and eighth columns of of Panels A, when utilizing the information contained in all the economic and technical predictors CP_t, LN_t, and $\tilde{\mathbf{F}}_t^{TI}$ together, the investor is willing to pay an even higher annualized portfolio management fee up to 2.50% over the 1975:01−2007:12 time period to have access to the five-year bond risk premium forecasts. If the technical indicators are ignored and only economic variables CP_t and LN_t are incorporated, the fee would sharply drop to 0.92%. Furthermore, the eighth column of of Panels B indicate that, over the 1985:01−2007:12 time period, the management fee can be as high as 4.21% for forecasts using all the information.

Panel C of Table 7 reports the utility gains for long-term government bonds with maturities from 17 to 20 years over the available 1985:01−2007:12 period. The third column of Panel C shows that all the forecasts based on CP_t generate positive utility gains for long-term government bonds, in the range of 0.45–0.77%. In contrast, none of the four forecasts based on LN_t deliver positive management fees. According to the second column of Panel C, all the utility gains of forecasts based on technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ are economically large for long-term bonds, ranging from 1.27% to 1.62%. However, when combining $\tilde{\mathbf{F}}_t^{TI}$ with CP_t and LN_t, the value is fairly limited for long-term bonds, and are in the 0.55–0.97% range as shown in the eighth column. Nevertheless, the technical indicators are still very important. Without them, the fee for the long-term government bond would drop to a economically undesirable range of -0.67–0.01% relative to the historical average forecast benchmark(see the seventh column of Panel C).

Overall, Table 7 shows that, while bond risk premia forecast based on CP_t generates limited economic value for short-term government bonds over 1975:01−2007:12 period, it generates fairly large value over the recent 1985:01−2007:12 period for both short- and long-term government bonds. But LN_t fails to produces economic value for either short- or long-term government bonds over either period. Forecasts based on technical indicators generally provides large utility gains for both short- and long-term bonds and over both 1975:01−2007:12 and 1985:01−2007:12 periods. In addition, forecasts utilizing all the information in economic variables and technical indicators together have much higher utility gains relative to the corresponding forecasts based on economic variables alone.

4 Conclusion

In this paper, we study the predictability of technical indicators for U.S. government bond risk premia, filling a gap of the literature that ignores this important part of information widely employed by traders and investors. We find that technical indicators have economically and statistically significant in- and out-of-sample forecasting power for both short- and long-term government bonds, and are (surprisingly) more useful as economic variables (those used today in academic studies). Moreover, forecasts combining information in technical indicators together with economic variables substantially outperform forecasts based on economic variables alone. From an asset allocation perspective, forecasts using all the information consistently generate significant economic values for allocating funds over either short- or long-term bonds over different periods, while forecasts based on economic variables alone frequently deliver small values or even losses.

This paper contributes to understanding why the bond market is much more predictable than the stock market in terms of R^2. We show that while the bond market is about 10 times as predictable as the stock market in term of R^2, the economic value accruing to bond market predictability is not 10 times profitable than the stock market, suggesting across the financial markets, the economic value of forecasting is likely the same due to perhaps across market arbitrage or intermarket efficiency. Our findings also call for new theories in understanding the predictability of bonds. Dai and Singleton(2002), Duffee (2002), Ang and Piazzesi (2003), Diebold and Li (2006), Diebold, Rudebusch, and Aruoba (2006), Duffee (2006), and Moench (2008), among others, incorporate economic variables into term structure modeling that shed insights on the predictability of the economic variables. However, none of the models take into account the role of technical indicators that are in the information set and used widely by traders and investors. We leave it for future research for developing new theories that uncover the role played by technical indicators in bond pricing.

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Table 1: Summary statistics for PC factors $\hat{f}_t$

This table reports the summary statistics for technical indicator PC factors $\hat{f}_{i,t}^{fs}$ and $\hat{f}_{i,t}^{OBV}$, which are estimated from 48 forward spread moving average technical indicators MA^{fs} and 15 trading volume technical indicators MA^{OBV}, respectively, using full sample of time-series information from 1964:01 to 2007:12. The first factor explains the largest fraction of the total variation in the technical indicators, where the total variation is defined as the sum of the variance of the individual technical indicators. And the *i*th factor explains the *i*th largest fraction of the total variation. The PC factors are mutually orthogonal. The number of factors is determined by the information criterion developed by Bai and Ng (2002). Column $AR1_i$ reports the first-order autocorrelation coefficients for technical PC factor i. Column R_i^2 shows the relative importance of the technical PC factor i, calculated by dividing the sum of the first i largest eigenvalues of the sample covariance matrix of the technical indicators to the sum of all eigenvalues.

	$\hat{f}_{i,t}^{fs}$		$\hat{f}_{i,t}^{OBV}$	
i	$AR1_i$	R_i^2	$AR1_i$	R_i^2
1	0.97	0.67	0.92	0.82
2	0.89	0.74	0.64	0.89
3	0.87	0.78	0.00	0.93
4	0.83	0.81	–	–
5	0.82	0.84	–	–

Table 2: In-sample forecasting results for excess returns of short-term Treasury bonds

This table reports the regression coefficients, heteroskedasticity and serial correlation robust t-statistics, and adjusted R^2 for in-sample predictive regression of log excess bond returns on the n-year short-term Treasury bond for $n = 2, ..., 5$ over the period 1964:01−2007:12. The dependent variable $rx_{t+1}^{(n)}$ is the log excess bond returns on the n-year Treasury bond. Forward spread moving average technical indicator factor $\hat{F}_{1,t}^{fs}$ and $\hat{F}_{3,t}^{fs}$, and trading volume technical indicator factor $\hat{F}_{1,t}^{OBV}$ are selected from PC factors estimated from 48 MA^{fs} trading rules based on the moving averages of two- to five-year forward spreads and 15 MA^{OBV} trading rules based on on-balance trading volume of stock market according to short-term government bonds and BIC criterion, respectively. Cochrane and Piazzesi (2005) forward rate factor CP_t, which is a linear combination of five forward rates, and Ludvigson and Ng (2009) macroeconomic variable factor LN_t, which is five PC factors estimated from a large panel of macroeconomic variables, are also included as control variables. Below each regression coefficient, Newey and West (1987) corrected t-statistics with 18 month lags are reported in parenthesis. A constant is always included in the regression specification though not reported in the table.

		$\hat{F}_{1,t}^{fs}$	$\hat{F}_{3,t}^{fs}$	$\hat{F}_{1,t}^{OBV}$	CP_t	LN_t	R^2
$rx_{t+1}^{(2)}$	(1)	1.09	0.62				0.28
		(4.84)	(3.89)				
	(2)			1.20			0.10
				(2.46)			
	(3)	1.02	0.54	0.81			0.28
		(4.26)	(3.88)	(1.89)			
	(4)	0.33	0.29		Yes	Yes	0.47
		(2.16)	(2.40)				
	(5)			0.79	Yes	Yes	0.48
				(2.02)			
	(6)	0.27	0.21	0.69	Yes	Yes	0.47
		(1.67)	(2.07)	(1.78)			
	(7)				Yes	Yes	0.45
	(8)				Yes		0.31
	(9)					Yes	0.23
$rx_{t+1}^{(3)}$	(1)	1.97	1.21				0.29
		(4.70)	(4.42)				
	(2)			2.12			0.10
				(2.33)			
	(3)	1.85	1.07	1.37			0.29
		(4.27)	(4.39)	(1.75)			
	(4)	0.66	0.59		Yes	Yes	0.46
		(2.26)	(2.76)				
	(5)			1.43	Yes	Yes	0.47
				(1.97)			
	(6)	0.55	0.46	1.22	Yes	Yes	0.46
		(1.81)	(2.47)	(1.69)			
	(7)				Yes	Yes	0.43
	(8)				Yes		0.33
	(9)					Yes	0.19
$rx_{t+1}^{(4)}$	(1)	2.74	1.79				0.32
		(4.72)	(4.75)				
	(2)			2.78			0.09
				(2.30)			
	(3)	2.59	1.63	1.68			0.32
		(4.35)	(4.64)	(1.68)			
	(4)	0.96	0.89		Yes	Yes	0.47
		(2.21)	(3.08)				
	(5)			1.85	Yes	Yes	0.47
				(1.97)			
	(6)	0.82	0.73	1.52	Yes	Yes	0.47
		(1.85)	(2.82)	(1.64)			
	(7)				Yes	Yes	0.44
	(8)				Yes		0.36
	(9)					Yes	0.16
$rx_{t+1}^{(5)}$	(1)	3.44	2.15				0.32
		(5.01)	(4.73)				
	(2)			3.21			0.08
				(2.19)			
	(3)	3.28	1.97	1.85			0.32
		(4.66)	(4.62)	(1.56)			
	(4)	1.51	1.18		Yes	Yes	0.44
		(2.77)	(3.19)				
	(5)			2.19	Yes	Yes	0.43
				(1.90)			
	(6)	1.37	0.99	1.72	Yes	Yes	0.44
		(2.43)	(2.99)	(1.52)			
	(7)				Yes	Yes	0.40
	(8)				Yes		0.33
	(9)					Yes	0.14

Table 3: In-sample forecasting results for excess returns of long-term Treasury bonds

This table reports the regression coefficients, heteroskedasticity and serial correlation robust t-statistics, and adjusted R^2 for in-sample predictive regression of log excess bond returns on the n-year long-term Treasury bond for $n = 17, ..., 20$ over the period 1982:07−2007:12. The dependent variable $rx_{t+1}^{(n)}$ is the log excess bond returns on the n-year Treasury bond. Forward spread moving average technical indicator factor $\hat{F}_{1,t}^{fs}$ and $\hat{F}_{3,t}^{fs}$, and trading volume technical indicator factor $\hat{F}_{1,t}^{OBV}$ are selected from PC factors estimated from 48 MA^{fs} trading rules based on the moving averages of two- to five-year forward spreads and 15 MA^{OBV} trading rules based on on-balance trading volume of stock market according to short-term government bonds and BIC criterion, respectively. Cochrane and Piazzesi (2005) forward rate factor CP_t, which is a linear combination of five forward rates, and Ludvigson and Ng (2009) macroeconomic variable factor LN_t, which is five PC factors estimated from a large panel of macroeconomic variables, are also included as control variables. Below each regression coefficient, Newey and West (1987) corrected t-statistics with 18 month lags are reported in parenthesis. A constant is always included in the regression specification though not reported in the table.

		$\hat{F}_{1,t}^{fs}$	$\hat{F}_{3,t}^{fs}$	$\hat{F}_{1,t}^{OBV}$	CP_t	LN_t	R^2
$rx_{t+1}^{(17)}$	(1)	9.27	9.68				0.45
		(3.55)	(5.69)				
	(2)			10.08			0.08
				(2.09)			
	(3)	9.01	9.51	1.32			0.45
		(2.91)	(5.55)	(0.38)			
	(4)	7.24	8.51		Yes	Yes	0.46
		(2.31)	(4.67)				
	(5)			8.41	Yes	Yes	0.31
				(2.57)			
	(6)	6.88	8.19	2.03	Yes	Yes	0.46
		(2.04)	(4.76)	(0.85)			
	(7)				Yes	Yes	0.27
	(8)				Yes		0.27
	(9)					Yes	0.05
$rx_{t+1}^{(18)}$	(1)	9.65	10.26				0.45
		(3.56)	(5.59)				
	(2)			10.17			0.07
				(2.01)			
	(3)	9.48	10.15	0.88			0.45
		(2.95)	(5.45)	(0.25)			
	(4)	7.57	9.02		Yes	Yes	0.46
		(2.32)	(4.66)				
	(5)			8.39	Yes	Yes	0.30
				(2.43)			
	(6)	7.30	8.77	1.57	Yes	Yes	0.46
		(2.09)	(4.74)	(0.62)			
	(7)				Yes	Yes	0.27
	(8)				Yes		0.27
	(9)					Yes	0.05
$rx_{t+1}^{(19)}$	(1)	10.01	10.84				0.45
		(3.57)	(5.47)				
	(2)			10.20			0.07
				(1.93)			
	(3)	9.94	10.79	0.38			0.45
		(3.00)	(5.32)	(0.10)			
	(4)	7.88	9.51		Yes	Yes	0.46
		(2.33)	(4.64)				
	(5)			8.30	Yes	Yes	0.30
				(2.29)			
	(6)	7.70	9.34	1.05	Yes	Yes	0.46
		(2.15)	(4.71)	(0.40)			
	(7)				Yes	Yes	0.27
	(8)				Yes		0.27
	(9)					Yes	0.05
$rx_{t+1}^{(20)}$	(1)	10.35	11.41				0.46
		(3.59)	(5.33)				
	(2)			10.15			0.06
				(1.87)			
	(3)	10.38	11.43	-0.19			0.46
		(3.05)	(5.18)	(-0.05)			
	(4)	8.17	9.99		Yes	Yes	0.47
		(2.33)	(4.61)				
	(5)			8.15	Yes	Yes	0.30
				(2.14)			
	(6)	8.08	9.91	0.48	Yes	Yes	0.47
		(2.20)	(4.66)	(0.17)			
	(7)				Yes	Yes	0.27
	(8)				Yes		0.28
	(9)					Yes	0.05

Table 4: Out-of-sample forecasting results for short-term Treasury bonds, 1975:01−2007:12

This table reports the out-of-sample R^2_{OS} statistics for log excess bond returns on the n-year short-term Treasury bond $rx^{(n)}_{t+1}$ for $n = 2,...,5$ over the 1975:01−2007:12 forecast evaluation period. R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for a predictive model based on predictors given in the column heading relative to historical average benchmark. $\tilde{F}_t$ represents three sets of technical indicator factors $\tilde{\mathbf{F}}^{fs}_t$, $\tilde{\mathbf{F}}^{OBV}_t$, and $\tilde{\mathbf{F}}^{TI}_t = (\tilde{\mathbf{F}}^{fs}_t, \tilde{\mathbf{F}}^{OBV}_t)$ reported in the Panel A, B, and C, respectively. Forward spread moving average technical indicator factor $\tilde{\mathbf{F}}^{fs}_t$ and trading volume technical indicator factor $\tilde{\mathbf{F}}^{OBV}_t$ are selected from PC factors estimated from 48 MA^{fs} trading rules based on the moving averages of two- to five-year bond forward spreads and 15 MA^{OBV} trading rules based on on-balance trading volume of stock market according to short-term government bonds and BIC criterion, respectively. CP_t and LN_t represent the Cochrane and Piazzesi (2005) forward rate factor and the Ludvigson and Ng (2009) macroeconomic variable factor, respectively. All factors and parameters are estimated recursively using only the information available through period of forecast formation t. The statistical significance of positive R^2_{OS} corresponding to H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$ is assessed using the Clark and West (2007) *MSPE-adjusted* statistics. *, **, and *** indicate significance at the 10%, 5%,and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
n	$\tilde{F}_t$	CP_t	$CP_t+\tilde{F}_t$	LN_t	$LN_t+\tilde{F}_t$	CP_t+LN_t	$CP_t+LN_t+\tilde{F}_t$
Panel A: Forward spread technical indicator factor, $\tilde{\mathbf{F}}^{fs}_t$							
2	0.229***	0.154**	0.255***	0.047**	0.269***	0.194***	0.291***
3	0.235***	0.152**	0.258***	0.001	0.266***	0.177**	0.287***
4	0.246***	0.179**	0.277***	−0.014	0.267***	0.190***	0.298***
5	0.252***	0.157**	0.276***	−0.042	0.265***	0.158**	0.289***
Panel B: Trading volume technical indicator factor, $\tilde{\mathbf{F}}^{OBV}_t$							
2	0.079**	0.154**	0.227***	0.047**	0.108**	0.194***	0.241***
3	0.071**	0.152**	0.210**	0.001	0.076**	0.177**	0.210**
4	0.060*	0.179**	0.228***	−0.014	0.054*	0.190***	0.219***
5	0.051*	0.157**	0.196***	−0.042	0.036*	0.158**	0.181**
Panel C: Forward spread and trading volume technical indicator factor, $\tilde{\mathbf{F}}^{TI}_t$							
2	0.256***	0.154**	0.302***	0.047**	0.298***	0.194***	0.332***
3	0.259***	0.152**	0.295***	0.001	0.289***	0.177**	0.317***
4	0.263***	0.179**	0.305***	−0.014	0.284***	0.190***	0.323***
5	0.263***	0.157**	0.295***	−0.042	0.278***	0.158**	0.307***

Table 5: Out-of-sample forecasting results for short-term Treasury bonds, 1985:01−2007:12

This table reports the out-of-sample R^2_{OS} statistics for log excess bond returns on the n-year short-term Treasury bond $rx^{(n)}_{t+1}$ for $n = 2,...,5$ over the 1985:01−2007:12 forecast evaluation period. R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for a predictive model based on predictors given in the column heading relative to historical average benchmark. $\tilde{F}_t$ represents three sets of technical indicator factors $\tilde{\mathbf{F}}^{fs}_t$, $\tilde{\mathbf{F}}^{OBV}_t$, and $\tilde{\mathbf{F}}^{TI}_t = (\tilde{\mathbf{F}}^{fs}_t, \tilde{\mathbf{F}}^{OBV}_t)$ reported in the Panel A, B, and C, respectively. Forward spread moving average technical indicator factor $\tilde{\mathbf{F}}^{fs}_t$ and trading volume technical indicator factor $\tilde{\mathbf{F}}^{OBV}_t$ are selected from PC factors estimated from 48 MA^{fs} trading rules based on the moving averages of two- to five-year bond forward spreads and 15 MA^{OBV} trading rules based on on-balance trading volume of stock market according to short-term government bonds and BIC criterion, respectively. CP_t and LN_t represent the Cochrane and Piazzesi (2005) forward rate factor and the Ludvigson and Ng (2009) macroeconomic variable factor, respectively. All factors and parameters are estimated recursively using only the information available through period of forecast formation t. The statistical significance of positive R^2_{OS} corresponding to H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$ is assessed using the Clark and West (2007) *MSPE-adjusted* statistics. *, **, and *** indicate significance at the 10%, 5%,and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
n	$\tilde{F}_t$	CP_t	$CP_t + \tilde{F}_t$	LN_t	$LN_t + \tilde{F}_t$	$CP_t + LN_t$	$CP_t + LN_t + \tilde{F}_t$
Panel A: Forward spread technical indicator factor, $\tilde{\mathbf{F}}^{fs}_t$							
2	0.256**	0.275*	0.331**	0.114*	0.340***	0.341***	0.415***
3	0.300**	0.276*	0.358**	0.099*	0.373***	0.344**	0.432***
4	0.329**	0.289**	0.379**	0.077*	0.389***	0.348**	0.440**
5	0.339***	0.273**	0.382**	0.053	0.383***	0.314**	0.427***
Panel B: Trading volume technical indicator factor, $\tilde{\mathbf{F}}^{OBV}_t$							
2	0.059*	0.275*	0.341**	0.114*	0.121**	0.341***	0.375***
3	0.056*	0.276*	0.333**	0.099*	0.113*	0.344**	0.372***
4	0.034*	0.289**	0.326**	0.077*	0.084*	0.348**	0.362**
5	0.024	0.273**	0.300**	0.053	0.059*	0.314**	0.323**
Panel C: Forward spread and trading volume technical indicator factor, $\tilde{\mathbf{F}}^{TI}_t$							
2	0.223***	0.275*	0.342***	0.114*	0.304***	0.341***	0.413***
3	0.273***	0.276*	0.372***	0.099*	0.339***	0.344**	0.432***
4	0.291***	0.289**	0.379**	0.077*	0.346***	0.348**	0.430***
5	0.296***	0.273**	0.369***	0.053	0.338***	0.314**	0.408***

Table 6: Out-of-sample forecasting results for long-term Treasury bonds, 1985:01−2007:12

This table reports the out-of-sample R^2_{OS} statistics for log excess bond returns on the n-year long-term Treasury bond $rx^{(n)}_{t+1}$ for $n = 17,\ldots,20$ over the 1985:01−2007:12 forecast evaluation period. R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for a predictive model based on predictors given in the column heading relative to historical average benchmark. $\tilde{F}_t$ represents three sets of technical indicator factors $\tilde{\mathbf{F}}^{fs}_t$, $\tilde{\mathbf{F}}^{OBV}_t$, and $\tilde{\mathbf{F}}^{TI}_t = (\tilde{\mathbf{F}}^{fs}_t, \tilde{\mathbf{F}}^{OBV}_t)$ reported in the Panel A, B, and C, respectively. Forward spread moving average technical indicator factor $\tilde{\mathbf{F}}^{fs}_t$ and trading volume technical indicator factor $\tilde{\mathbf{F}}^{OBV}_t$ are selected from PC factors estimated from 48 MA^{fs} trading rules based on the moving averages of two- to five-year bond forward spreads and 15 MA^{OBV} trading rules based on on-balance trading volume of stock market according to short-term government bonds and BIC criterion, respectively. CP_t and LN_t represent the Cochrane and Piazzesi (2005) forward rate factor and the Ludvigson and Ng (2009) macroeconomic variable factor, respectively. All factors and parameters are estimated recursively using only the information available through period of forecast formation t. The statistical significance of positive R^2_{OS} corresponding to H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$ is assessed using the Clark and West (2007) *MSPE-adjusted* statistics. *, **, and *** indicate significance at the 10%, 5%,and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
n	$\tilde{F}_t$	CP_t	$CP_t+\tilde{F}_t$	LN_t	$LN_t+\tilde{F}_t$	CP_t+LN_t	$CP_t+LN_t+\tilde{F}_t$
Panel A: Forward spread technical indicator factor, $\tilde{\mathbf{F}}^{fs}_t$							
17	0.394***	0.234***	0.417**	−0.196	0.282***	0.044***	0.282***
18	0.411**	0.235***	0.424**	−0.182	0.300**	0.060***	0.300***
19	0.427**	0.238***	0.432**	−0.167	0.319**	0.078***	0.319***
20	0.440**	0.240***	0.440**	−0.150	0.338**	0.097***	0.338***
Panel B: Trading volume technical indicator factor, $\tilde{\mathbf{F}}^{OBV}_t$							
17	−0.214	0.234***	0.064***	−0.196	−0.227	0.044***	0.027***
18	−0.213	0.235***	0.068***	−0.182	−0.224	0.060***	0.030***
19	−0.208	0.238***	0.074***	−0.167	−0.219	0.078***	0.036***
20	−0.201	0.240***	0.083***	−0.150	−0.211	0.097***	0.044***
Panel C: Forward spread and trading volume technical indicator factor, $\tilde{\mathbf{F}}^{TI}_t$							
17	0.172**	0.234***	0.202***	−0.196	0.194***	0.044***	0.201***
18	0.183**	0.235***	0.214***	−0.182	0.207***	0.060***	0.214***
19	0.196**	0.238***	0.228***	−0.167	0.223***	0.078***	0.228***
20	0.211**	0.240***	0.244***	−0.150	0.240***	0.097***	0.244***

Table 7: Asset allocation results

This table reports the average utility gains for a mean-variance investor with risk aversion coefficient of three who allocates between 1-year risk-free Treasury bill and n-year Treasury bond. Utility gain is the portfolio management fee (in annualized percent return) that an investor would be willing to pay to have access to the out-of-sample predictive regression forecasts based on the predictors given in the column heading relative to the historical average benchmark forecast. Forward spread and trading volume technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ is selected from PC factors estimated from 48 MA^{fs} trading rules based on the moving averages of two- to five-year bond forward spreads and 15 MA^{OBV} trading rules based on on-balance trading volume of stock market according to short-term government bonds and BIC criterion. CP_t and LN_t represent the Cochrane and Piazzesi (2005) forward rate factor and the Ludvigson and Ng (2009) macroeconomic variable factor, respectively. All factors and parameters are estimated recursively using only the information available through period of forecast formation t. Panel A and B report the average utility gains of short-term bonds with maturities $n = 2, \ldots, 5$ over 1975:01−2007:12 and 1985:01−2007:12 forecast evaluation periods, respectively, and Panel C reports the average utility gains of long-term bonds with maturities $n = 17, \ldots, 20$ over 1985:01−2007:12 period.

(1) n	(2) $\tilde{\mathbf{F}}_t^{TI}$	(3) CP_t	(4) $CP_t + \tilde{\mathbf{F}}_t^{TI}$	(5) LN_t	(6) $LN_t + \tilde{\mathbf{F}}_t^{TI}$	(7) $CP_t + LN_t$	(8) $CP_t + LN_t + \tilde{\mathbf{F}}_t^{TI}$
Panel A: Short-term Treasury bonds, 1975:01−2007:12							
2	1.04	-0.87	0.69	-0.57	1.61	-0.46	1.04
3	1.38	-0.37	1.14	-0.80	1.85	-0.07	1.37
4	1.58	0.07	1.50	-0.89	1.88	0.32	1.65
5	2.26	0.70	2.34	-0.53	2.44	0.92	2.50
Panel B: Short-term Treasury bonds, 1985:01−2007:12							
2	1.08	0.32	1.32	-0.07	1.52	0.79	1.65
3	2.09	1.32	2.40	0.01	2.49	1.73	2.50
4	3.01	2.18	3.23	0.23	3.20	2.59	3.20
5	4.12	3.07	4.26	0.73	4.13	3.42	4.21
Panel C: Long-term Treasury bonds, 1985:01−2007:12							
17	1.27	0.45	0.61	-1.96	1.23	-0.67	0.55
18	1.45	0.58	0.81	-1.87	1.47	-0.44	0.76
19	1.59	0.70	0.95	-1.74	1.67	-0.20	0.92
20	1.62	0.77	1.00	-1.61	1.78	0.01	0.97