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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 statistically and economically significant in- and out-of-sample forecasting power. Moreover, we find that utilizing information from both technical indicators and economic variables substantially increases the forecasting performances relative to using just economic variables.

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

Keywords: Bond risk premium predictability; Economic variables; Technical analysis; Moving-average rules; Volume; Out-of-sample forecasts; Principal components

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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 statistically and economically significant in- and out-of-sample forecasting power. Moreover, we find that utilizing information from both technical indicators and economic variables substantially increases the forecasting performances relative to using just economic variables.

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1 Introduction

There are a number of important studies that use various financial and macroeconomic variables to predict the excess returns of U.S. government bonds. For example, Fama and Bliss (1987) present evidence that the *n*-year forward spread predicts *n*-year excess bond returns. Keim and Stambaugh (1986), Fama and French (1989), and Campbell and Shiller (1991) find that yield spreads predict excess bond returns. Ilmanen (1995) find bond risk premia predictability based on macroeconomic variables across countries. Baker, Greenwood, and Wurgler (2003) detect predictability for the maturity of new debt issues. More recently, Cochrane and Piazzesi (2005) find that a linear combination of five forward rates predicts the excess bond returns with R^2 between 30% and 35% for bonds with maturities ranging from two to five years. Ludvigson and Ng (2009) find that five macroeconomic factors estimated from a large number of macroeconomic variables have significant predictive power on bond risk premia even in the presence of forward rates and yield spreads. Duffee (2011) uncovers that a hidden factor which negatively covaries with aggregate economic activity has substantial forecasting power for excess bond returns. These studies suggest that bond market risk premia are time-varying and seem correlated with macroeconomic conditions.[1]

While the bond risk premia predictability literature has investigated the predictive ability of using the various economic predictors, such as forward rates (e.g., Cochrane and Piazzesi, 2005) and macroeconomic variables (e.g., Ludvigson and Ng, 2009), it pays little attention to the use of technical indicators, such as moving-average trading indicators. But these indicators are easily available and 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). In the stock market, although early studies (e.g., Cowles, 1933; Fama and Blume, 1966; Jensen and Benington, 1970) typically find little ability for technical indicators to forecast future stock returns, recent studies by Brock, Lakonishok, and LeBaron (1992), Brown,

[1] Wachter (2006) shows that Campbell and Cochrane (1999) habit-formation model should explain the time varying bond risk premia. Brandt and Wang (2003) argue that bond risk premia are driven by inflation as well as aggregate consumption. Bansal and Shaliastovich (2010) provide a Bansal and Yaron (2004) long-run risk based model, and show that time-varying macroeconomic (i.e., consumption) volatility explains the predictability in bond risk premia based on economic predictors. However, it is not clear to what extent these models can account for the forecasting ability of technical indicators for bond risk premia.

Goetzmann, and Kumar (1998), Allen and Karjalainen (1999), Sullivan, Timmermann, and White (1999), Lo, Mamaysky, and Wang (2000), Savin, Weller, and Zvingelis (2007), and Neely, Rapach, Tu and Zhou (2011), among others, find that technical indicators do have forecasting power.[2] This paper provides perhaps the first such a study in the bond market. 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?

We use 48 technical indicators constructed in the standard way based on forward spread moving averages. Since the bond market trading volume data are unavailable to us, we construct 15 technical indicators based on stock market trading volume.[3] 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; 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 significant concern, and it most likely delivers very poor out-of-sample forecasting performance.[4] To avoid model over-fitting, we, following Ludvigson and Ng (2007, 2009), generate bond risk premia forecasts based on the predictive regression with 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 Cochrane and Piazzesi's (2005) and Ludvigson and Ng's (2009) factors. Our in-sample analysis confirms a strong predictive power of the technical indicators.

However, out-of-sample tests 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

[2]In foreign exchange markets, academic studies generally find stronger support for the predictability of technical analysis. For example, LeBaron (1999) and Neely (2002) show that moving averages generate substantial portfolio gains for currency trading and that the gains are much larger than those in the stock market. Moreover, Menkhoff and Taylor (2007) argue that technical analysis today is as important as fundamental analysis to currency mangers.

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

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

the stock market prediction.[5] We study the out-of-sample predictive ability of technical indicators based on the Campbell and Thompson's (2008) out-of-sample R^2 statistic, R^2_{OS}, which measures the reduction in mean squared predictive error (MSPE). We transform the technical indicator factors into bond risk premia forecasts using a recursive factor-augmented predictive regression, and calculate R^2_{OS} statistics for the competing out-of-sample forecasts based on technical indicator factor, $\tilde{F}_t$, relative to four restricted benchmarks which exclude the technical indicator factor:[6]

First, to assess the out-of-sample predictive power of using technical indicators alone, we calculate the R^2_{OS} statistics for a competing model including constant and technical indicator factor $\tilde{F}_t$ relative to a historical average benchmark corresponding to the constant expected return model.

Second, to assess the additional out-of-sample predictive power of technical indicators beyond that contained in forward rate factor CP_t, we calculate the R^2_{OS} statistics for a competing model including constant, CP_t and $\tilde{F}_t$ relative to a restricted benchmark model which only includes constant and CP_t.

Third, to assess the incremental out-of-sample predictive power of technical indicators beyond that contained in macroeconomic variable factor LN_t, we calculate the R^2_{OS} statistics for a competing model including constant, LN_t and $\tilde{F}_t$, relative to a restricted benchmark model which only includes constant and LN_t.

Fourth, to assess the incremental out-of-sample predictive power of technical indicators beyond that contained in forward rate factor CP_t and macroeconomic variable factor LN_t, we calculate the R^2_{OS} statistics for a competing model including constant, CP_t, LN_t and $\tilde{F}_t$ relative to a restricted benchmark model which only includes constant, CP_t and LN_t.

Moreover, we also examine the economic value of the out-of-sample bond risk premia forecasts based on technical indicators from an asset allocation perspective. Specifically, we calculate the utility gain for a mean-variance investor who optimally allocates a portfolio between n-year Treasury bond $rx^{(n)}_{t+1}$ and one-year risk-free bill using out-of-sample excess bond return forecasts generated by a competing predictive model which includes technical indicators relative to an investor who uses the restricted out-of-sample forecasts which exclude technical indicators. While numerous studies investigate the profitability of technical indicators, these studies are *ad hoc* in that they do not account for the investor's risk aversion in the asset allocation decision. Similar to Zhu and Zhou (2009) and Neely, Rapach, Tu and Zhou (2011), we avoids this drawback and

[5]See Lettau and Ludvigson (2009) for literature review on in-sample versus out-of-sample asset return predictability.

[6]To avoid look-ahead bias, at time t, we implement recursively predictive regressions in forecasting bond premia with all factors, such as $\tilde{F}_t$, CP_t, and LN_t, and parameters estimated using information available only up t.

compare the utility gains for a risk-averse investor who forecasts the bond risk premia based on technical indicators relative to an identical investor who forecasts the bond risk premia not using the technical indicators.

Empirically, we find strong predictive power of technical indicators for bond risk premia. In particular, the technical PC factors alone explain up to 35% of the variation of bond risk premia for bonds with various maturities ranging from two to five years. In addition, we find that including technical indicator factors on top of CP_t and LN_t can increase the adjusted R^2 significantly (e.g., from 39% to 46% for the case of bonds with a maturity of five years). Furthermore, the regression coefficients for both the forward spread moving average technical indicator factors and volume technical indicator factors are economically large and statistically significant at reasonable levels. These results indicate that the technical indicators tracking bond and stock markets contain useful forecasting information for bond risk premia beyond that is contained in the economic variables, such as forward rates and macroeconomic variables.

Our out-of-sample analysis based on R^2_{OS} statistic and utility gain metrics reinforce the conclusion that technical indicators are useful for predicting bond risk premia. The R^2_{OS} statistics relative to all of the four benchmarks are found to be economically large, statistically significant and stable over time. For example, the R^2_{OS} statistics for the out-of-sample excess bond return forecasts based on technical PC factors relative to the fourth benchmark model, which includes constant, CP_t and LN_t as predictors, range from 25.4% to 28.9% over the 1975:01−2007:12 out-of-sample evaluation period depending on bonds' maturities.

Our mean-variance asset allocation study shows that bond risk premia predictability based on technical indicators generates substantial economic gains for the investor. For example, a mean-variance investor with a risk aversion coefficient of five is willing to pay an annualized portfolio management fee of 3.47% to have access to five-year excess bond return forecast utilizing the information contained in the technical indicators and economic variables relative to the restricted benchmark that uses just the economic predictors over the 1975:01−2007:12 forecast evaluation period.

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 forward spread 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:[7]

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

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 ($s < l$).[8] 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 forward rates.[9] For example, when the n-year forward rates

[7] The technical indicators based on forward spread moving average capture the trend-following idea at the center of technical analysis.

[8] 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.

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

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).[10] 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

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

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. 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 (forward spread moving average 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.,

[10] 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, the predictive power becomes much less once the Ludvigson and Ng (2009) LN_t factor is included in the predictive regression. A potential explanation is that the forecasting information in these technical indicators 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.

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; Stock and Watson, 2002a, 2002b; Ludvigson and Ng, 2007, 2009, 2011).

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 $rx_{t+1}^{(n)}$:

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

where $\hat{F}_t \subset \hat{f}_t$, is a subset selected based on some criterion detailed later. (6) 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.

It is important to distinguish between $\hat{F}_t$ and $\hat{f}_t$, because the pervasive factors in $\hat{f}_t$ may not be relevant in predicting excess bond returns $rx_{t+1}^{(n)}$. Following Stock and Watson (2002b) and 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 $\hat{f}_t$. We first form different subsets of $\hat{f}_t$. We then regress $rx_{t+1}^{(n)}$ on a candidate subset, $\hat{F}_t$, and Z_t, and compute the corresponding BIC for each candidate subset of factors, $\hat{F}_t$. The preferred set of technical indicators factors $\hat{F}_t$ is determined by minimizing the BIC. We then report results for technical indicator PC factor $\hat{F}_t$.

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, 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 current time, t.[11]

First, we generate an out-of-sample principle component forecast of excess bond return $rx_{t+1}^{(n)}$ based on out-of-sample 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 $\tilde{F}_t \subset \tilde{f}_t$, and $\tilde{\alpha}_t$ is a least squares estimate of α in (6) by regressing $\{rx_{(k/12)+1}^{(n)}\}_{k=1}^{12(t-1)}$ on $\{\tilde{F}_{k/12}\}_{k=1}^{12(t-1)}$. The preferred subset of out-of-sample technical indicator factors $\{\tilde{F}_{k/12}\}_{k=1}^{12t}$ is selected from the different subsets of technical indicator PC factors $\{\tilde{f}_{k/12}\}_{k=1}^{12t}$, using the BIC criterion and information available through period t. We form different subsets of $\{\tilde{f}_{k/12}\}_{k=1}^{12t}$. For each candidate set of factors, $\{\tilde{F}_{k/12}\}_{k=1}^{12t}$, we regress $\{rx_{(k/12)+1}^{(n)}\}_{k=1}^{12(t-1)}$ on $\{\tilde{F}_{k/12}\}_{k=1}^{12(t-1)}$ and $\{Z_{k/12}\}_{k=1}^{12(t-1)}$ and compute the corresponding BIC. We then choose the preferred set of factors $\{\tilde{F}_{k/12}\}_{k=1}^{12t}$ with minimum BIC. 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: $\{\widetilde{rx}_{k/12}^{(n)}\}_{k=m+1}^{12T}$.[12] The historical average of excess bond returns, $\overline{rx}_{t+1}^{(n)} = \frac{1}{12t}\sum_{k=1}^{12t} rx_{k/12}^{(n)}$,

[11] 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.

[12] 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

is the restricted forecast benchmark corresponding to the constant expected excess return model (restricting $\alpha = 0$ in (6)).

To assess whether technical indicators have incremental out-of-sample predictive ability for excess bond return $rx_{t+1}^{(n)}$ beyond that contained in economic predictors, we then generate an out-of-sample principle component 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 (Equation (7)) using information through 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 and Ludvigson and Ng (2009) macroeconomic factor LN_t, and $\tilde{\alpha}_t$ 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: $\{\widetilde{rx}_{k/12}^{(n)}\}_{k=m+1}^{12T}$. To assess the incremental out-of-sample predictive ability of technical indicators, we choose the restricted version of (9) as a out-of-sample forecast benchmark which only utilizes the information in economic predictor Z_t (setting $\alpha = 0$ in (7)):

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

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

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

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

where $rx_{k/12}^{(n)}$ represents the excess log return on n-year Treasury bond during period $k/12$, $\widetilde{rx}_{k/12}^{(n)}$ represents a competing out-of-sample forecast for $rx_{k/12}^{(n)}$ based on technical indicator factor $\tilde{F}_t$ and the information through period $(k/12)-1$, and $\widetilde{rx}_{k/12}^{(n),R}$ represents the corresponding restricted out-

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.

of-sample forecast benchmark which excludes technical indicator factor. Thus, when $R^2_{OS} > 0$, the competing forecast using technical indicators outperforms the restricted forecast benchmark not using technical indicators 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 : $R^2_{OS} > 0$.[13] 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.[14] Comparing the competing forecast based on technical indicator factors with the corresponding restricted benchmark entails comparing nested models, since setting $\alpha = 0$ in Equation (8) and (9) yields the restricted forecast benchmarks.

Specifically, we calculate the R^2_{OS} statistics for the technical indicator factor $\tilde{F}_t$ by comparing the competing forecasts including technical indicator factor $\tilde{F}_t$ with the the following four restricted predictive benchmarks: (1) We calculate the R^2_{OS} statistics for a model specification including $\tilde{F}_t$ and constant as predictors in Equation (8) relative to the historical average benchmark corresponding to the constant expected return model for assessing the out-of-sample predictive power of using technical indicators alone. (2) We calculate the R^2_{OS} statistics for a model specification including $\tilde{F}_t$, Cocharane and Piazzesi (2005's factor CP_t and constant (Equation (9)) relative to the benchmark model including only constant and CP_t (Equation (10)) for assessing the additional out-of-sample predictive power of technical indicators beyond that contained in CP_t. (3) We calculate the R^2_{OS} statistics for a model specification including $\tilde{F}_t$, Ludvigson and Ng (2009)'s factor LN_t and constant relative to the benchmark model including only constant and LN_t for assessing the incremental out-of-sample predictive power of technical indicators beyond that contained in LN_t. (4) We calculate the R^2_{OS} statistics for a model specification including $\tilde{F}_t$, Cocharane and Piazzesi (2005)'s factor CP_t, Ludvigson and Ng (2009)'s factor LN_t and constant relative to the benchmark model including only constant, CP_t and LN_t for assessing the incremental out-of-sample predictive power of technical indicators beyond that contained in CP_t and LN_t.

Asset allocation provides another perspective for assessing the economic significance of out-

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

[14]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.

of-sample predictability based on technical indicators.[15] 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) and Thornton and Valente (2010). 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 five 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 indicator PC factors as predictors versus a benchmark model not including technical indicator PC factors as predictors. 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 (e.g., the forecast based on technical indicators alone or the forecast based on technical indicators and economic variables), and $\tilde{\sigma}_{t+1}^{(n),2}$ is a forecast of the excess n-year bond return variance.[16] Following Campbell and Thompson (2008), we assume that the investor uses a five-year moving window of past excess bond returns to estimate the variance. The average utility for the investor who incorporates information contained in the technical indictors into the predictive model of excess n-year bond return is given by

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

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

[15]For example, Thornton and Valente (2010), among others, show that, although forward rates and yields have statistically significant forecasting ability for excess bond returns, they generate little economic value for the investor from asset allocation perspective. Duffee (2010) indicates that in-sample over-fitting leads to astronomically high implied Sharpe ratios.

[16]To limit the impact of estimation error, we impose an upper bound of 8 to the absolute portfolio weight. Imposing other upper bounds generates similar results. Utility would be larger if we relaxed the portfolio weight constraint in the asset allocation problem.

the last q monthly out-of-sample evaluation samples. We then calculate the average utility for the same investor who instead uses the restricted forecast benchmark which excludes technical indicators (e.g., the historical average forecast or the forecast based on economic variables alone) to predict the excess n-year bond return. At the end of period t, the investor allocates

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

to n-year Treasury bond during period $t+1$, where $\widetilde{rx}_{t+1}^{(n),R}$ is a restricted forecast for $rx_{t+1}^{(n)}$ which excludes the technical indicators. The investor then realizes an average utility of

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

during the out-of-sample evaluation period, where $\hat{\mu}_R^{(n)}$ and $\hat{\sigma}_R^{(n),2}$ are the sample mean and variance, respectively, for the the portfolio in Equation (14) formed using the sequence of restricted forecasts $\widetilde{rx}_{t+1}^{(n),R}$. The utility gain accruing to the technical indicators is the difference between (13) and (15), $\hat{v}^{(n)} - \hat{v}_R^{(n)}$. The utility gain 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 relative to the the restricted predictive benchmark $\widetilde{rx}_{t+1}^{(n),R}$ which excludes the technical indicators.

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 bond returns using technical indicators.

3.1 Data

Our monthly data span 1964:01−2007:12.[17] We compute the annual bond returns, forward rates and yields using the Fama-Bliss data at a monthly frequency as described in Section (2.1). The Fama-Bliss data of one- through five-year zero coupon U.S. Treasury bond prices are available from the Center for Research in Securities Prices (CRSP). The macroeconomic fundamentals data

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

used in Ludvigson and Ng (2009, 2011) are from Sydney C. Ludvigson's web page.[18] We use the monthly forward spreads when computing the forward spread moving average technical indicator in Equation (1). In addition, we use monthly stock market trading volume data from Google Finance to compute the trading volume-based trading signal 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.[19] $\hat{f}_t^{fs}$ 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 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 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.[20] 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.[21] 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% 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

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

[19] 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.

[20] 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.

[21] 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.

coefficients for moving average technical factors $\hat{f}_t^{fs}$ and trading volume technical factors $\hat{f}_t^{OBV}$ range from 0.82 to 0.97 and from 0.00 to 0.92, respectively.[22]

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

Following Cochrane and Piazzesi (2005), we also consider the predictive power of a single linear combination of the selected three-factor technical predictor $\hat{\mathbf{F}}_t^{TI} = (\hat{\mathbf{F}}_t^{fs}, \hat{\mathbf{F}}_t^{OBV}) = (\hat{F}_{1,t}^{fs}, \hat{F}_{3,t}^{fs}, \hat{F}_{1,t}^{OBV})$. This single factor denoted $F3_t$ is defined as $\hat{\eta}'\hat{\mathbf{F}}_t^{TI}$, where the 3×1 vector of slope coefficients, $\hat{\eta}$, is estimated by running the following predictive regression of the average (across maturity) excess bond returns $\overline{rx}_{t+1}$ on the three selected technical indicator factors in $\hat{\mathbf{F}}_t^{TI}$:

$$\overline{rx}_{t+1} = \eta_0 + \eta_1 \hat{F}_{1,t}^{fs} + \eta_2 \hat{F}_{3,t}^{fs} + \eta_3 \hat{F}_{1,t}^{OBV} + u_{t+1}. \tag{16}$$

The estimated values and robust t-statistics of η is presented in Table 2.

3.2 In-sample analysis

Table 3 reports regression slope coefficients, heteroskedasticity and serial correlation robust t-statistics, and adjusted R^2 for in-sample predictive regression of log excess bond returns on lagged technical indicator factors over the full sample period 1964:01−2007:12.[23] 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. Equations (6) and (7) examine separately the in-sample predictive power of technical indicator factors for excess bond returns not including and including the economic predictors, and the results are reported in rows 1 through 4 and rows 5 through 8, respectively. To test the incremental

[22]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.

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

predictive power of technical factors beyond that contained in the economic predictors, CP_t and LN_t, Cochrane and Piazzesi (2005) factor and Ludvigson and Ng (2009) factor, are included in Z_t of Equation (7) as conditioning variables. The in-sample forecasting results of using CP_t and LN_t alone are reported in Row 9 as a benchmark.

Rows 1 to 4 of the top panel $rx_{t+1}^{(2)}$ of Table 3 report the in-sample predictive regression results for two-year excess bond returns $rx_{t+1}^{(2)}$ based on technical indicator PC factors. Row 1 shows that the forward spread moving average trading rules have significant predictive power for $rx_{t+1}^{(2)}$. The first and third PC factors based on forward spread moving average trading signals, $\hat{F}_{1,t}^{fs}$ and $\hat{F}_{3,t}^{fs}$, are statistically significant at the 1% or better level. These two technical PC factors alone explain 28% of the two-year bond excess return variation. According to Row 2, the trading volume-based trading signals are also significant predictors for $rx_{t+1}^{(2)}$. The first PC factor $\hat{F}_{1,t}^{OBV}$ is statistically significant at the 5% level, with adjusted R^2 of 10%. Row 3 shows that, when all of the three technical indicator PC factors contained in $\hat{\mathbf{F}}_t^{TI}$ are included in a predictive regression, the adjusted R^2 would rise to 32%, with all factors statistically significant at the conventional level. Thus, both the forward spread moving average and trading volume-based technical indicators are useful in predicting two-year excess bond returns.

We turn next to examine whether the technical indicators have incremental predictive power for two-year excess bond returns beyond that contained in economic predictors such as the forward rate factor CP_t and macroeconomic variable factor LN_t. Rows 5 through 8 of the top panel $rx_{t+1}^{(2)}$ in Table 3 show that the technical indicator factors have significant predictive power even in the presence of CP_t and LN_t. Almost all the technical PC factors are statistically significant at reasonable level. In addition, the inclusion of three technical indicator PC factors contained in $\hat{\mathbf{F}}_t^{TI}$ on top of CP_t and LN_t would improve the adjusted R^2 from 44% to 50%. Row 8 shows that when the single-factor $F3_t$ (a linear combination of the three individual technical indicator PC factors contained in $\hat{\mathbf{F}}_t^{TI}$) is added into the predictive regression on top of CP_t and LN_t, the $F3_t$ has significant predictive power at the 1% level and increase $\bar{R}^2$ from 44% to 49%. These results indicate that the technical indicators contain useful forecasting information beyond that contained in forward rates, yields, and macroeconomic variables. Hence, adding the technical indicator factors to economic predictors such as CP_t and LN_t significantly enhances the excess bond return predictability.

Rows 4 and 8 of Table 3, Panel $rx_{t+1}^{(2)}$ shows that the single-factor predictor $F3_t$ has almost the same predictive power as do the competing models that include the three technical PC factors contained in $\hat{\mathbf{F}}_t^{TI}$ as separate predictors. For example, both $F3_t$ and $\hat{\mathbf{F}}_t^{TI}$ alone yield the same sizable adjusted R^2 of 32% in predicting $rx_{t+1}^{(2)}$. Including $F3_t$ or $\hat{\mathbf{F}}_t^{TI}$ with CP_t and LN_t in predictive regression produce almost the same large adjusted R^2 of 49% and 50%, respectively. These results are similar to those reported in Cochrane and Piazzesi (2005), and indicate that a single technical indicator factor could summarize all the forecasting information in technical indicators.

A closer look at the technical indicator factors find that both forward spread moving average technical indicators and trading volume technical indicators are important predictors for excess bond returns. Follow Ludvigson and Ng (2009), we evaluate the relative importance of technical indicator factors in $\hat{\mathbf{F}}_t^{TI}$ by analyzing the absolute value of regression coefficients in Equations (7) and (16). Tables 2 and 3 show that all of the three technical PC factors have economically large coefficients in absolute value. Thus both the forward spread moving average and trading volume-based technical indicators are important predictors for excess bond returns.

The remaining panels of Table 3 show that technical indicator factors have strong in-sample forecasting power for excess bond returns 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 $\bar{R}^2$ up to 35%. Moreover, The technical indicators have significant predictive power for excess bond returns of each maturity even in presence of economic predictors such as 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 $\bar{R}^2$ significantly from 39% to 46% for the five-year excess bond returns, with almost all the technical indicator factors statistically significant. The predictive power of the single-factor predictor $F3_t$ for excess bond returns is very similar to that of the competing model that includes the three technical indicator factors in $\hat{\mathbf{F}}_t^{TI}$ as separate predictors. The regression coefficients of the single-factor predictor $F3_t$ increase monotonically as bond maturities increase, with statistical significance at the 1% or better level. In summary, the technical indicators contain significant forecasting information that is not contained in the economic variables, the technical indicator factors and the economic predictors together generate economically large excess bond returns predictability.

3.3 R_{OS}^2 statistics

Table 4 reports the Campbell and Thompson (2008) R_{OS}^2 statistics for out-of-sample excess bond return forecasts of maturities of two-, three-, four-, and five years based on technical indicator factors $\tilde{F}_t$ over the 1975:01−2007:12 out-of-sample forecast evaluation period. The out-of-sample technical indicator factor $\tilde{F}_t$ represents three groups of technical factors: $\tilde{\mathbf{F}}_t^{fs}$, $\tilde{\mathbf{F}}_t^{OBV}$, and $\tilde{\mathbf{F}}_t^{TI} =$

($\tilde{\mathbf{F}}_t^{fs}$, $\tilde{\mathbf{F}}_t^{OBV}$), where $\tilde{\mathbf{F}}_t^{fs} \subset \tilde{f}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV} \subset \tilde{f}_t^{OBV}$ are selected according to the out-of-sample BIC criterion, and $\tilde{f}_t^{fs}$ and $\tilde{f}_t^{OBV}$ are PC factors estimated from 48 MA^{fs} rules and 15 MA^{OBV} rules, respectively.[24] All the factors, such as $\tilde{f}_t^{fs}$, $\tilde{f}_t^{OBV}$, CP_t, and LN_t, and parameters are estimated recursively using only the information available through period t.

The R^2_{OS} statistics for the technical indicators relative to four benchmarks are reported in Table 4: Rows *const* report the R^2_{OS} statistics for a competing model including technical indicator factor $\tilde{F}_t$ as predictors in Equation (8) relative to the historical average benchmark corresponding to the restricted constant expected return model. Rows $const + CP_t$ report the R^2_{OS} statistics for the competing model including technical indicator factor $\tilde{F}_t$ and CP_t as predictors in Equation (9) relative to the restricted benchmark model including only a constant and CP_t in Equation (10). Rows $const + LN_t$ report the R^2_{OS} statistics for the competing model including technical indicator factor $\tilde{F}_t$ and LN_t as predictors relative to the restricted benchmark model including only a constant and LN_t. Rows $const + CP_t + LN_t$ report the R^2_{OS} statistics for a competing model including technical indicator factor $\tilde{F}_t$, CP_t and LN_t as predictors relative to the restricted benchmark model including only a constant, CP_t and LN_t. The statistical significance of positive R^2_{OS} is assessed with the Clark and West (2007) *MSPE-adjusted* statistics, as discussed in Section (2.3)

According to Row *const* of Table 4, all of the three sets of technical indicator PC factors produce sizable R^2_{OS} statistics relative to the historical average benchmark for excess bond returns of all maturities over the 1975:01−2007:12 out-of-sample forecast evaluation period, so that they outperform the historical average benchmark in term of MSPE. Column $\tilde{\mathbf{F}}_t^{TI}$ of Table 4, Row *const* shows that technical factor $\tilde{\mathbf{F}}_t^{TI}$ have R^2_{OS} up to 26.8%. The sizable R^2_{OS} statistics for $rx^{(2)}_{t+1}$,..., $rx^{(5)}_{t+1}$ are significant at 1% or better level, indicating that technical indicators have economically large and statistically significant out-of-sample predictive power for excess bond returns relative to the historical average benchmark. Furthermore, Columns $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ of Table 4, Row *const* demonstrate that both the forward spread moving average and trading volume-based trading rules are useful in predicting out-of-sample bond risk premia. For example, $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ generate R^2_{OS} up to 25.2% and 7.4%, respectively, with statistical significance at the 5% or better level. These results suggest that, similar to the conclusions reached in the Section (3.2), technical indicators have important out-of-sample predictive power for excess bond returns.

Rows $const + CP_t$, $const + LN_t$, and $const + CP_t + LN_t$ of Table 4 provide evidence on the incremental out-of-sample predictive power of technical indicators beyond that contained in the eco-

[24]Specifications that select predictors factors, $\tilde{F}_t^{(n)}$, separately for individual bonds of two-, three-, four-, and five-year maturities generate nearly the same results.

nomic predictors such as CP_t and LN_t over the 1975:01−2007:12 out-of-sample forecast evaluation period. Row $const + CP_t + LN_t$ of Table 4, Column $\tilde{\mathbf{F}}_t^{TI}$ shows that a competing model including the technical factor $\tilde{\mathbf{F}}_t^{TI}$, CP_t, and LN_t improves significantly relative to the restricted predictive benchmark that only includes a constant, CP_t, and LN_t in term of MSPE. The R_{OS}^2 statistics are from 25.4% to 28.9%, which are economically large and statistically significant at 5% level. In addition, Row $const + CP_t$ (Row $const + LN_t$) of Table 4, Column $\tilde{\mathbf{F}}_t^{TI}$ show that a competing model including the technical factor $\tilde{\mathbf{F}}_t^{TI}$ and CP_t (LN_t) improves significantly relative to the restricted predictive benchmark that only includes a constant and CP_t (LN_t). These results reinforce the conclusion that including technical indicators and economic predictors together would substantially improve the out-of-sample predictability of bond risk premia relative to the benchmark that only uses the economic predictors.

Columns $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ show that both the forward spread moving average and trading volume-based trading rules yield large R_{OS}^2 relative to the restricted benchmark that only includes economic predictors. For example, The R_{OS}^2 statistics of $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ relative to the benchmark forecast including CP_t and LN_t are up to 26.2% and 4.5%, respectively, which are significant at the 5% level. Thus, both bond forward spread moving average and trading volume-based technical indicators have strong out-of-sample predictive power for excess bond returns beyond that contained in economic predictors such as CP_t and LN_t.

Comparing the results in Columns $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ of Table 4, the forward spread moving average technical indicators and trading volume technical indicators contain generally complementary forecasting information. Columns $\tilde{\mathbf{F}}_t^{OBV}$ of Table 4 shows that $\tilde{\mathbf{F}}_t^{OBV}$ has relatively more predictive power for short-maturity excess bond returns, with almost all the R_{OS}^2 based on $\tilde{\mathbf{F}}_t^{OBV}$ for five-year excess bond returns smaller than those for two-year excess bond returns. In contrast, Columns $\tilde{\mathbf{F}}_t^{fs}$ of Table 4 shows that $\tilde{\mathbf{F}}_t^{fs}$ has relatively higher forecasting ability for excess bond returns with long-maturity than those with short-maturity. Furthermore, Column $\tilde{\mathbf{F}}_t^{TI}$ shows that forecasts utilizing information from both $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ almost always substantially outperform the forecasts based on $\tilde{\mathbf{F}}_t^{fs}$ or $\tilde{\mathbf{F}}_t^{OBV}$ alone. Taken together, the results in Table 4 highlight the relevance of both the forward spread moving average and trading volume-based technical indicators in forecasting bond risk premia.

To see whether the predictability of technical indicators vary over time, Table 5 and 6 report the R_{OS}^2 statistics of technical indicator factors over 1985:01−2007:12 and 1975:01−2003:12 (2003:12 matches the ending month of the sample period used in Cochrane and Piazzesi (2005)) out-of-sample evaluation periods, respectively. Although there are some variation across time, technical indicator factors consistently produce economically and statistically significant out-of-sample forecasting gains relative to each benchmark for excess bond returns of all maturities. For example, technical indicators factor $\tilde{\mathbf{F}}_t^{TI}$ have sizable R^2_{OS} statistics of 29.6% and 28.0% for five-year excess bond returns relative to historical average benchmark over the 1985:01−2007:12 and 1975:01−2003:12 out-of-sample evaluation periods, respectively. Both of the R^2_{OS} statistics are significant at the 1% level. According to Row $const + CP_t + LN_t$, forecasts including technical indicators factor $\tilde{\mathbf{F}}_t^{TI}$, CP_t, and LN_t increase the out-of-sample forecasting performance by 13.9% and 29.9% for five-year excess bond returns relative to the restricted forecasting benchmarks only using the CP_t and LN_t over the 1985:01−2007:12 and 1975:01−2003:12 evaluation periods, respectively.

3.4 Asset Allocation

Table 7 reports the out-of-sample asset allocation results for a mean-variance investor with risk aversion coefficient of five who allocates between 1-year risk-free bill and two-, three-, four-, and five-year Treasury bonds, respectively, based on information through period t over the 1975:01−2007:12 out-of-sample evaluation period. We first compute the average utilities, in annualized percent, for the portfolios constructed using the competing forecasting model including the technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ (Panel A of Table 7), and the average utilities for the portfolios formed using the restricted forecasting model which excludes $\tilde{\mathbf{F}}_t^{TI}$ (Panel B of Table 7), respectively. The utility gains in Panel C are then the difference between the average utilities in Panels A and B, which measure the change in average utilities from predicting $rx_{t+1}^{(n)}$ with the competing forecasts instead of the restricted forecasts. 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 forecast, which uses the information contained in the technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$, vis-á-vis the restricted benchmark forecast. Similar to the R^2_{OS} in Section (3.3), we assess the economic value of the technical indicators relative to four sets of restricted benchmarks as follows: the constant expected return model (Row *const*), the model including a constant and CP_t (Row $const + CP_t$), the model including a constant and LN_t (Row $const + LN_t$), and the model including a constant, CP_t, and LN_t (Row $const + CP_t + LN_t$).

According to Row *const* of Table 7, Panel B, the annualized average utilities for the constant expected return model go from −0.46% ($rx_{t+1}^{(2)}$) to −1.13% ($rx_{t+1}^{(5)}$), indicating that an investor who relies on the historical average forecasts would suffer utility losses up to -1.13%. Row *const* of Table 7, Panel A shows the portfolios based on a competing model, which adds the technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ to the constant term, have higher annualized average utilities, ranging from 2.34% to 2.69%. Thus the investor would be willing to pay a sizable annual management fee up to 3.82% to have access to the competing forecasts based on technical indicators vis-á-vis the historical average forecasts, as indicated in Row *const* of Table 7, Panel C.

Row $const + CP_t$ of Table 7, Panel B shows that a restricted benchmark model including a constant and the Cochrane and Piazzesi (2005) forward rate factor CP_t also generates large negative average utilities. Comparing the results in Rows *const* and $const + CP_t$ of Table 7, Panel B, although CP_t has statistically significant forecasting power for excess bond returns (e.g., Cochrane and Piazzesi, 2005), it generates little economic value in term of utility gain from a asset allocation perspective, as reported by Thornton and Valente (2010) as well. In contrast, Row *const* of Table 7, Panel A indicates that the portfolios based on a competing model, which includes a constant, CP_t and $\tilde{\mathbf{F}}_t^{TI}$, realize sizable average utilities up to 2.11%. Again, as presented in Row $const + CP_t$ of Table 7, Panel C, economically large gains accrue to an investor from adding the technical indicator factor to the restricted benchmark model only including a constant and CP_t.

Observe from Row $const + LN_t$ of Table 7, Panel B that, the average utilities of the portfolios based on the a restricted benchmark model including a constant and the Ludvigson and Ng (2009) macroeconomic factor LN_t are almost always larger than those of the portfolios based on the historical average forecasts. From this perspective, LN_t contains economically relevant information for predicting the bond risk premia. However, there are still three out of four portfolios with negative average utilities. In contrast, Row $const + LN_t$ of Table 7, Panel A shows that all of the portfolios based on a competing model including a constant, LN_t and $\tilde{\mathbf{F}}_t^{TI}$ provide large positive average utilities. In fact, it generates the largest average utility in Table 9 of 3.65% on two-year Treasury bond, $rx_{t+1}^{(2)}$. Hence, as indicated in the Row $const + LN_t$ of Table 7, Panel C, the competing model incorporating information contained in both LN_t and $\tilde{\mathbf{F}}_t^{TI}$ provides economically significant utility gains beyond the restricted benchmark model only utilizing information in LN_t.

Row $const + CP_t + LN_t$ of Table 7, Panel B indicates that three out of four portfolios based on the a restricted benchmark model including a constant, CP_t and LN_t have negative average utilities, and they are better that those of the portfolios based on CP_t alone and worse than those of the portfolios based on LN_t alone. In contrast, Row $const + CP_t + LN_t$ of Table 7, Panel A shows that all of the average utilities of portfolios based on the competing model, utilizing information contained in CP_t, LN_t and $\tilde{\mathbf{F}}_t^{TI}$, are once again positive and economically large. The utility gains from using the forecasts based on a competing model instead of the forecasts based on a restricted benchmark model, reported in Row $const + CP_t + LN_t$ of Table 7, Panel C, are thus economically sizable, ranging from 3.07% to 3.47%. Therefore, the investor would be willing to pay a annual management fee up to 3.47% to have access to the competing forecasts including technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ on top of CP_t and LN_t vis-á-vis the restricted benchmark model excluding $\tilde{\mathbf{F}}_t^{TI}$.

Overall, Table 7 shows that bond risk premia forecasts based on the competing model, which adds the technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ upon the benchmark predictors, usually produce economically sizable utility gains, relative to the forecasts based on the restricted benchmark model which only includes the benchmark predictors. These findings highlight the economic significance of bond risk premia predictability using technical indicators. Analogous to the finding by Thornton and Valente (2010), we also find that Cochrane and Piazzesi (2005) forward rate factor CP_t provides little economic value in term of utility gain. This may explain the fact that the third competing predictive model, which includes a constant term, LN_t and $\tilde{\mathbf{F}}_t^{TI}$, tends to realize the highest average utilities, particulary on bonds with short-maturity, over the 1975:01$-$2007:12 out-of-sample evaluation period.

4 Conclusion

In this paper, we study the predictability of the U.S. bond risk premia by using technical indicators, filling a gap of the literature that ignores this important part of information widely employed by traders and investors. We compare the predictive power of the technical indictors to economic variables based on both in- and out-of-sample analysis. We find that technical indicators have economically and statistically significant in- and out-of-sample forecasting power. Moreover, principal component forecasts that combining information from both technical indicators and economic variables substantially outperform the forecasts of using the economic variables alone. Economically, a mean-variance investor with a risk aversion coefficient of five is willing to pay an annualized portfolio management fee of 3.47% to have access to the bond return forecast utilizing the information contained in the technical indicators and economic variables relative to the restricted benchmark that uses only the economic predictors over the 1975:01$-$2007:12 forecast evaluation period.

Our results suggest several avenues for future research. For instance, what economic forces do the technical indictors capture beyond those captured by the commonly used economic variables? In addition, how can the bond predictability be consistent with the expectation hypothesis in the bond literature and what term structure models can be designed to take into account this predictability?[25]

[25]There are some studies incorporating the bond risk premia predictability based on economic variables into term structure models, such as Dai and Singleton(2002), Duffee (2002), Ang and Piazzesi (2003), Ang, Piazzesi, and Wei (2006), Diebold and Li (2006), Diebold, Rudebusch, and Aruoba (2006), Duffee (2006), and Moench (2008).

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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 $\hat{f}^{fs}_{i,t}$ and $\hat{f}^{OBV}_{i,t}$, which are estimated from 48 forward spread moving average technical indicators and 15 trading volume technical indicators, 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 ith factor explains the ith 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^2_i shows the relative importance of the technical PC factor i, calculated by dividing the sum of the first i largest eigenvalues of xx', the sample covariance matrix of the technical indicators, to the sum of all eigenvalues.

	$\hat{f}^{fs}_{i,t}$		$\hat{f}^{OBV}_{i,t}$	
i	$AR1_i$	R^2_i	$AR1_i$	R^2_i
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: Estimates of the single-factor predictor $F3_t$

This table reports the estimates of the single-factor technical indicator predictor $F3_t$ from predictive regression (16) (below) of average (across maturity) excess bond returns $\overline{rx}_{t+1}$ on the preferred subset of three technical indicator factors $\hat{\mathbf{F}}_t^{TI} = (\hat{F}_{1,t}^{fs}, \hat{F}_{3,t}^{fs}, \hat{F}_{1,t}^{OBV})$, which are selected by minimizing the BIC criterion across all of possible specifications based on $(\hat{f}_t^{fs}, \hat{f}_t^{OBV})$ using the data from 1964:01 to 2007:12.

$$\overline{rx}_{t+1} = \eta_0 + \eta_1 \hat{F}_{1,t}^{fs} + \eta_2 \hat{F}_{3,t}^{fs} + \eta_3 \hat{F}_{1,t}^{OBV} + u_{t+1}.$$

$\hat{\eta}$ and $t_{\hat{\eta}}$ columns report the regression coefficients and Newey-West (1987) corrected t-statistics with 18 month lags, respectively.

	$\hat{\eta}$	$t_{\hat{\eta}}$
$\hat{F}_{1,t}^{fs}$	-2.18	-4.48
$\hat{F}_{3,t}^{fs}$	1.30	4.52
$\hat{F}_{1,t}^{OBV}$	1.43	1.69
R^2	0.35	

Table 3: In-sample log excess bond returns forecasting results

This table reports the regression coefficients, heteroskedasticity and serial correlation robust t-statistics, and adjusted R^2 for in-sample predictive regression of $rx_{t+1}^{(n)}$ for $n = 2, ..., 5$ in Equation (7) 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. The technical indicator factors $\hat{F}_{1,t}^{fs}$, $\hat{F}_{3,t}^{fs}$, and $\hat{F}_{1,t}^{OBV}$ are estimated by the PC method from 48 MA^{fs} rules and 15 MA^{OBV} rules, respectively. $F3_t$ is the single factor constructed as the linear combination of the three technical indicator PC factors as described in Equation (16) and Table 2. The conditioning variable Z_t contains the Cochrane and Piazzesi (2005) factor CP_t and Ludvigson and Ng (2009) factor LN_t. CP_t is a linear combination of five forward rates, and LN_t is five PC factors estimated from a large panel of macroeconomic 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 it is not reported in the table.

		$\hat{F}_{1,t}^{fs}$	$\hat{F}_{3,t}^{fs}$	$\hat{F}_{1,t}^{OBV}$	$F3_t$	CP_t	LN_t	R^2
	(1)	-1.09	0.62			No	No	0.28
		(-4.84)	(3.89)					
	(2)			1.20		No	No	0.10
				(2.46)				
	(3)	-1.02	0.54	0.81		No	No	0.32
		(-4.26)	(3.88)	(1.89)				
$rx_{t+1}^{(2)}$	(4)				0.46	No	No	0.32
					(6.68)			
	(5)	-0.33	0.29			Yes	Yes	0.47
		(-2.17)	(2.40)					
	(6)			0.79		Yes	Yes	0.48
				(2.02)				
	(7)	-0.27	0.21	0.70		Yes	Yes	0.50
		(-1.70)	(2.07)	(1.78)				
	(8)				0.21	Yes	Yes	0.49
					(3.20)			
	(9)					Yes	Yes	0.44
	(1)	-1.98	1.21			No	No	0.29
		(-4.70)	(4.42)					
	(2)			2.12		No	No	0.10
				(2.33)				
	(3)	-1.85	1.07	1.37		No	No	0.33
		(-4.27)	(4.39)	(1.76)				
$rx_{t+1}^{(3)}$	(4)				0.86	No	No	0.33
					(6.80)			
	(5)	-0.66	0.59			Yes	Yes	0.46
		(-2.26)	(2.76)					
	(6)			1.43		Yes	Yes	0.47
				(1.97)				
	(7)	-0.55	0.46	1.23		Yes	Yes	0.49
		(-1.82)	(2.48)	(1.69)				
	(8)				0.41	Yes	Yes	0.48
					(3.49)			
	(9)					Yes	Yes	0.43
	(1)	-2.74	1.79			No	No	0.32
		(-4.72)	(4.75)					
	(2)			2.78		No	No	0.09
				(2.30)				
	(3)	-2.59	1.63	1.68		No	No	0.35
		(-4.34)	(4.64)	(1.68)				
$rx_{t+1}^{(4)}$	(4)				1.21	No	No	0.35
					(6.94)			
	(5)	-0.96	0.89			Yes	Yes	0.47
		(-2.21)	(3.08)					
	(6)			1.85		Yes	Yes	0.47
				(1.98)				
	(7)	-0.83	073	1.53		Yes	Yes	0.49
		(-1.86)	(2.82)	(1.65)				
	(8)				0.59	Yes	Yes	0.49
					(3.67)			
	(9)					Yes	Yes	0.44
	(1)	-3.44	2.15			No	No	0.32
		(-5.01)	(4.73)					
	(2)			3.21		No	No	0.08
				(2.19)				
	(3)	-3.28	1.98	1.85		No	No	0.34
		(-4.66)	(4.62)	(1.60)				
$rx_{t+1}^{(5)}$	(4)				1.47	No	No	0.35
					(7.04)			
	(5)	-1.52	1.18			Yes	Yes	0.44
		(-2.76)	3.19					
	(6)			2.19		Yes	Yes	0.43
				(1.90)				
	(7)	-1.37	0.99	1.72		Yes	Yes	0.46
		(-2.43)	(2.98)	(1.52)				
	(8)				0.80	Yes	Yes	0.46
					(3.89)			
	(9)					Yes	Yes	0.39

Table 4: Out-of-sample log excess bond returns forecasting results, 1975:01−2007:12

This table reports the out-of-sample R^2_{OS} statistics of technical indicator factor $\tilde{F}_t$ for log excess bond returns on the n-year Treasury bond, $rx^{(n)}_{t+1}$. R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for a competing predictive model, which includes the benchmark predictors given in the first column and technical indicator factor $\tilde{F}_t$ together, relative to the restricted forecast benchmark which only includes the benchmark predictors. R^2_{OS} statistics is computed for the 1975:01−2007:12 forecast evaluation period. Rows *const* report the R^2_{OS} statistics for a competing forecast based on a constant and technical indicator factor $\tilde{F}_t$ relative to historical average benchmark corresponding to the constant expected return model. Rows $const + CP_t$ report the R^2_{OS} statistics for a competing forecast based on a constant, CP_t, and $\tilde{F}_t$ relative to restricted benchmark based on just a constant and CP_t. Rows $const + LN_t$ report the R^2_{OS} statistics for the competing model, which includes a constant, LN_t, and $\tilde{F}_t$, relative to the restricted benchmark model including only a constant and LN_t. Rows $const + CP_t + LN_t$ report the R^2_{OS} statistics for the competing model, which includes a constant, CP_t, LN_t and $\tilde{F}_t$, relative to the restricted benchmark model including only a constant, CP_t and LN_t. *const*, CP_t, and LN_t represent the constant term, the Cochrane and Piazzesi (2005) forward rate factor, and the Ludvigson and Ng (2009) macroeconomic variable factor, respectively. The $\tilde{F}_t$ represents technical indicator factors $\tilde{\mathbf{F}}^{fs}_t$, $\tilde{\mathbf{F}}^{OBV}_t$, and $\tilde{\mathbf{F}}^{TI}_t = (\tilde{\mathbf{F}}^{fs}_t, \tilde{\mathbf{F}}^{OBV}_t)$ given in the first row, respectively. Those technical PC factors $\tilde{\mathbf{F}}^{fs}_t \subset \tilde{f}^{fs}_t$ and $\tilde{\mathbf{F}}^{OBV}_t \subset \tilde{f}^{OBV}_t$ are selected according to the out-of-sample BIC criterion, where $\tilde{f}^{fs}_t$ and $\tilde{f}^{OBV}_t$ are PC factors estimated from 48 MA^{fs} rules and 15 MA^{OBV} rules, respectively. All factors and parameters are estimated recursively using only the information available through period t. The p-value of Clark and West (2007) *MSPE-adjusted* statistics is reported in parenthesis which assesses the statistical significance of positive R^2_{OS} corresponding to H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$.

Benchmark predictors	$\tilde{\mathbf{F}}^{fs}_t$	$\tilde{\mathbf{F}}^{OBV}_t$	$\tilde{\mathbf{F}}^{TI}_t$
	$rx^{(2)}_{t+1}$		
const	0.229	0.074	0.263
	(0.000)	(0.015)	(0.000)
$const + CP_t$	0.142	0.109	0.201
	(0.000)	(0.012)	(0.000)
$const + LN_t$	0.234	0.035	0.260
	(0.001)	(0.039)	(0.000)
$const + CP_t + LN_t$	0.213	0.045	0.254
	(0.037)	(0.023)	(0.019)
	$rx^{(3)}_{t+1}$		
const	0.235	0.065	0.264
	(0.000)	(0.021)	(0.000)
$const + CP_t$	0.133	0.076	0.178
	(0.000)	(0.035)	(0.000)
$const + LN_t$	0.244	0.029	0.268
	(0.000)	(0.053)	(0.000)
$const + CP_t + LN_t$	0.228	0.039	0.263
	(0.039)	(0.046)	(0.027)
	$rx^{(4)}_{t+1}$		
const	0.246	0.054	0.268
	(0.000)	(0.030)	(0.000)
$const + CP_t$	0.119	0.058	0.157
	(0.001)	(0.045)	(0.000)
$const + LN_t$	0.254	0.025	0.274
	(0.001)	(0.063)	(0.000)
$const + CP_t + LN_t$	0.239	0.039	0.271
	(0.043)	(0.050)	(0.032)
	$rx^{(5)}_{t+1}$		
const	0.252	0.044	0.268
	(0.000)	(0.041)	(0.000)
$const + CP_t$	0.128	0.030	0.153
	(0.001)	(0.079)	(0.000)
$const + LN_t$	0.260	0.022	0.278
	(0.000)	(0.072)	(0.000)
$const + CP_t + LN_t$	0.262	0.036	0.289
	(0.036)	(0.063)	(0.029)

Table 5: Out-of-sample log excess bond returns forecasting results, 1985:01−2007:12

This table reports the out-of-sample R^2_{OS} statistics of technical indicator factor $\tilde{F}_t$ for log excess bond returns on the n-year Treasury bond, $rx^{(n)}_{t+1}$. R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for a competing predictive model, which includes the benchmark predictors given in the first column and technical indicator factor $\tilde{F}_t$ together, relative to the restricted forecast benchmark which only includes the benchmark predictors. R^2_{OS} statistics is computed for the 1985:01−2007:12 forecast evaluation period. Rows *const* report the R^2_{OS} statistics for a competing forecast based on a constant and technical indicator factor $\tilde{F}_t$ relative to historical average benchmark corresponding to the constant expected return model. Rows $const+CP_t$ report the R^2_{OS} statistics for a competing forecast based on a constant, CP_t, and $\tilde{F}_t$ relative to restricted benchmark based on just a constant and CP_t. Rows $const+LN_t$ report the R^2_{OS} statistics for the competing model, which includes a constant, LN_t, and $\tilde{F}_t$, relative to the restricted benchmark model including only a constant and LN_t. Rows $const+CP_t+LN_t$ report the R^2_{OS} statistics for the competing model, which includes a constant, CP_t, LN_t and $\tilde{F}_t$, relative to the restricted benchmark model including only a constant, CP_t and LN_t. *const*, CP_t, and LN_t represent the constant term, the Cochrane and Piazzesi (2005) forward rate factor, and the Ludvigson and Ng (2009) macroeconomic variable factor, respectively. The $\tilde{F}_t$ represents technical indicator factors $\tilde{\mathbf{F}}^{fs}_t$, $\tilde{\mathbf{F}}^{OBV}_t$, and $\tilde{\mathbf{F}}^{TI}_t = (\tilde{\mathbf{F}}^{fs}_t, \tilde{\mathbf{F}}^{OBV}_t)$ given in the first row, respectively. Those technical PC factors $\tilde{\mathbf{F}}^{fs}_t \subset \tilde{f}^{fs}_t$ and $\tilde{\mathbf{F}}^{OBV}_t \subset \tilde{f}^{OBV}_t$ are selected according to the out-of-sample BIC criterion, where $\tilde{f}^{fs}_t$ and $\tilde{f}^{OBV}_t$ are PC factors estimated from 48 MA^{fs} rules and 15 MA^{OBV} rules, respectively. All factors and parameters are estimated recursively using only the information available through period t. The p-value of Clark and West (2007) *MSPE-adjusted* statistics is reported in parenthesis which assesses the statistical significance of positive R^2_{OS} corresponding to H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$.

Benchmark predictors	$\tilde{\mathbf{F}}^{fs}_t$	$\tilde{\mathbf{F}}^{OBV}_t$	$\tilde{\mathbf{F}}^{TI}_t$
	$rx^{(2)}_{t+1}$		
const	0.256	0.059	0.223
	(0.006)	(0.053)	(0.002)
$const+CP_t$	0.146	0.159	0.160
	(0.000)	(0.026)	(0.003)
$const+LN_t$	0.249	0.036	0.216
	(0.016)	(0.082)	(0.012)
$const+CP_t+LN_t$	0.101	0.061	0.111
	(0.003)	(0.058)	(0.005)
	$rx^{(3)}_{t+1}$		
const	0.300	0.056	0.273
	(0.004)	(0.061)	(0.001)
$const+CP_t$	0.149	0.115	0.167
	(0.000)	(0.043)	(0.002)
$const+LN_t$	0.293	0.032	0.263
	(0.010)	(0.083)	(0.006)
$const+CP_t+LN_t$	0.125	0.052	0.136
	(0.001)	(0.074)	(0.003)
	$rx^{(4)}_{t+1}$		
const	0.329	0.034	0.291
	(0.004)	(0.088)	(0.002)
$const+CP_t$	0.128	0.053	0.127
	(0.000)	(0.103)	(0.004)
$const+LN_t$	0.320	0.014	0.280
	(0.009)	(0.126)	(0.006)
$const+CP_t+LN_t$	0.137	0.031	0.129
	(0.000)	(0.113)	(0.003)
	$rx^{(5)}_{t+1}$		
const	0.339	0.024	0.296
	(0.003)	(0.106)	(0.001)
$const+CP_t$	0.106	-0.012	0.087
	(0.001)	(0.254)	(0.006)
$const+LN_t$	0.331	0.009	0.289
	(0.005)	(0.139)	(0.004)
$const+CP_t+LN_t$	0.159	0.021	0.139
	(0.000)	(0.134)	(0.001)

Table 6: Out-of-sample log excess bond returns forecasting results, 1975:01−2003:12

This table reports the out-of-sample R^2_{OS} statistics of technical indicator factor $\tilde{F}_t$ for log excess bond returns on the n-year Treasury bond, $rx^{(n)}_{t+1}$. R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for a competing predictive model, which includes the benchmark predictors given in the first column and technical indicator factor $\tilde{F}_t$ together, relative to the restricted forecast benchmark which only includes the benchmark predictors. R^2_{OS} statistics is computed for the 1975:01−2003:12 forecast evaluation period. Rows *const* report the R^2_{OS} statistics for a competing forecast based on a constant and technical indicator factor $\tilde{F}_t$ relative to historical average benchmark corresponding to the constant expected return model. Rows $const + CP_t$ report the R^2_{OS} statistics for a competing forecast based on a constant, CP_t, and $\tilde{F}_t$ relative to restricted benchmark based on just a constant and CP_t. Rows $const + LN_t$ report the R^2_{OS} statistics for the competing model, which includes a constant, LN_t, and $\tilde{F}_t$, relative to the restricted benchmark model including only a constant and LN_t. Rows $const + CP_t + LN_t$ report the R^2_{OS} statistics for the competing model, which includes a constant, CP_t, LN_t and $\tilde{F}_t$, relative to the restricted benchmark model including only a constant, CP_t and LN_t. *const*, CP_t, and LN_t represent the constant term, the Cochrane and Piazzesi (2005) forward rate factor, and the Ludvigson and Ng (2009) macroeconomic variable factor, respectively. The $\tilde{F}_t$ represents technical indicator factors $\tilde{\mathbf{F}}^{fs}_t$, $\tilde{\mathbf{F}}^{OBV}_t$, and $\tilde{\mathbf{F}}^{TI}_t = (\tilde{\mathbf{F}}^{fs}_t, \tilde{\mathbf{F}}^{OBV}_t)$ given in the first row, respectively. Those technical PC factors $\tilde{\mathbf{F}}^{fs}_t \subset \tilde{f}^{fs}_t$ and $\tilde{\mathbf{F}}^{OBV}_t \subset \tilde{f}^{OBV}_t$ are selected according to the out-of-sample BIC criterion, where $\tilde{f}^{fs}_t$ and $\tilde{f}^{OBV}_t$ are PC factors estimated from 48 MA^{fs} rules and 15 MA^{OBV} rules, respectively. All factors and parameters are estimated recursively using only the information available through period t. The p-value of Clark and West (2007) *MSPE-adjusted* statistics is reported in parenthesis which assesses the statistical significance of positive R^2_{OS} corresponding to H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$.

Benchmark predictors	$\tilde{\mathbf{F}}^{fs}_t$	$\tilde{\mathbf{F}}^{OBV}_t$	$\tilde{\mathbf{F}}^{TI}_t$
	$rx^{(2)}_{t+1}$		
const	0.236	0.072	0.268
	(0.000)	(0.024)	(0.000)
$const + CP_t$	0.148	0.111	0.207
	(0.000)	(0.013)	(0.000)
$const + LN_t$	0.242	0.034	0.266
	(0.001)	(0.052)	(0.000)
$const + CP_t + LN_t$	0.218	0.048	0.260
	(0.035)	(0.023)	(0.018)
	$rx^{(3)}_{t+1}$		
const	0.245	0.065	0.273
	(0.000)	(0.028)	(0.000)
$const + CP_t$	0.138	0.080	0.186
	(0.000)	(0.035)	(0.000)
$const + LN_t$	0.253	0.029	0.277
	(0.000)	(0.065)	(0.000)
$const + CP_t + LN_t$	0.233	0.044	0.270
	(0.038)	(0.042)	(0.026)
	$rx^{(4)}_{t+1}$		
const	0.257	0.056	0.279
	(0.000)	(0.036)	(0.000)
$const + CP_t$	0.124	0.066	0.166
	(0.001)	(0.038)	(0.000)
$const + LN_t$	0.264	0.026	0.284
	(0.001)	(0.071)	(0.000)
$const + CP_t + LN_t$	0.245	0.045	0.280
	(0.043)	(0.041)	(0.031)
	$rx^{(5)}_{t+1}$		
const	0.263	0.048	0.280
	(0.000)	(0.044)	(0.000)
$const + CP_t$	0.134	0.042	0.165
	(0.001)	(0.057)	(0.000)
$const + LN_t$	0.269	0.025	0.288
	(0.000)	(0.073)	(0.000)
$const + CP_t + LN_t$	0.267	0.043	0.299
	(0.037)	(0.048)	(0.028)

Table 7: Asset allocation results, 1975:01–2007:12

This table reports the out-of-sample asset allocation results of the technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ for a mean-variance investor with risk aversion coefficient of five who allocates between 1-year risk-free bill and two-, three-, four- , and five-year Treasury bonds, respectively, based on information through period t over the 1975:01−2007:12 out-of-sample evaluation period. Panels A and B present the average utilities, in annualized percent, for the portfolios constructed using the competing forecasting model, which adds the technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ to the benchmark predictors given in the first column, and the average utilities for the portfolios constructed using the restricted benchmark model which only includes the benchmark predictors given in the first column, respectively. The average utility gains in Panel C represent the difference between the average utilities in Panels A and B, which measure the change in average utilities from predicting $rx_{t+1}^{(n)}$ with the competing forecast instead of the restricted forecast. 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 forecast vis-á-vis the restricted benchmark forecast. We assess the economic value of utilizing the technical indicators to predict the bond risk premia relative to the following four sets of restricted benchmarks: the constant expected return model (Row *const*), the model including a constant and CP_t (Row $const+CP_t$), the model including a constant and LN_t (Row $const+LN_t$), and the model including a constant,CP_t, and LN_t (Row $const+CP_t+LN_t$), where *const*, CP_t, and LN_t represent the constant term, the Cochrane and Piazzesi (2005) forward rate factor, and the Ludvigson and Ng (2009) macroeconomic variable factor, respectively. Columns $rx_{t+1}^{(2)}$,..., $rx_{t+1}^{(5)}$ report the asset allocation results for the investor who allocates across 1-year risk-free bill and two-, three-, four-, five-year Treasury bonds, respectively. $\tilde{\mathbf{F}}_t^{TI}$ denotes the the vector of factors ($\tilde{\mathbf{F}}_t^{fs}$, $\tilde{\mathbf{F}}_t^{OBV}$), where $\tilde{\mathbf{F}}_t^{fs} \subset \tilde{f}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV} \subset \tilde{f}_t^{OBV}$ are selected according to the out-of-sample BIC criterion, and $\tilde{f}_t^{fs}$ and $\tilde{f}_t^{OBV}$ are PC factors estimated from 48 MA^{fs} rules and 15 MA^{OBV} rules, respectively. All factors and parameters are estimated recursively using only the information available through period t.

Benchmark predictors	$rx_{t+1}^{(2)}$	$rx_{t+1}^{(3)}$	$rx_{t+1}^{(4)}$	$rx_{t+1}^{(5)}$
Panel A: Average utilities based on competing models				
const	2.48	2.61	2.35	2.69
$const+CP_t$	2.11	1.57	0.77	1.40
$const+LN_t$	3.65	3.23	1.83	1.72
$const+CP_t+LN_t$	3.46	2.23	0.90	1.16
Panel B: Average utilities based on restricted benchmark models				
const	-0.46	-0.52	-0.77	-1.13
$const+CP_t$	-2.80	-2.77	-3.06	-2.77
$const+LN_t$	0.84	-0.02	-0.80	-0.73
$const+CP_t+LN_t$	0.39	-1.10	-2.36	-2.31
Panel C: Utility gains				
const	2.94	3.13	3.12	3.82
$const+CP_t$	4.91	4.34	3.83	4.17
$const+LN_t$	2.80	3.25	2.63	2.44
$const+CP_t+LN_t$	3.07	3.33	3.27	3.47