Forecasting Government Bond Risk Premia Using Technical Indicators

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Abstract

While economic variables have been used extensively to forecast bond risk premia, little attention has been paid to technical indicators which are widely used by practitioners. In this paper, we study the predictive ability of a variety of technical indicators vis-á-vis the economic variables. We find that technical indicators have significant in both in- and out-of-sample forecasting power. Moreover, we find that using information from both technical indicators and economic variables increases the forecasting performance substantially. We also find that the economic value of bond risk premia forecasts from our methodology is comparable to that of equity risk premium forecasts.

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

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I. Introduction

The ability to predict interest rates movements are important to market participants such as bond investors, policy makers, and financial economists. For the policy makers, understanding of the evolution of future interest rates will aid the fine turning of macroeconomic monetary policies. For the bond investors, understanding interest rates predictability may translate into higher bond returns performance.

There are numerous studies that use various financial and macroeconomic variables to predict the excess returns and bond risk premia on U.S.government bonds. For examples, 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 similar predictive power too. In the international markets, Ilmanen (1995) find models using macroeconomic variables can forecast bond risk premia.

More recently, based on a linear combination of five forward rates, Cochrane and Piazzesi (2005) find much higher predictive power in terms of R^2, between 30% and 35%. Their study focused on 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 upon using five macroeconomic factors that are estimated from a set of 132 macroeconomic variables.

In this paper, we study the forecasting power of a new set of bond risk premia predictors. We use technical indicators (past price/volume patterns) constructed from both the bond and stock market as the set of predictors. Studies that use technical indicators as predictors of stock returns date back to Cowles (1933) and they are still being studied today. For example, 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 evidence supporting technical indicators having significant forecasting power on the equity risk premium. Perhaps, this may be one of the reasons why technical indicators are widely employed by traders and investors (e.g., Schwager, 1989, 1992, 2012; Billingsley and Chance, 1996; Covel, 2005; Park and Irwin, 2007; Lo and Hasanhodzic, 2010) to discern market trends.[1]

Despite the voluminous amount of research in the forecasting power of technical indicators in the equity market, to the best of our knowledge, this is the first paper that examines the usefulness of technical indicators in the bond market. In bridging this equity-bond market gap, we seek to answer two questions: (1) Do technical indicators provide useful information in forecasting bond risk premia? (2) Do combinations of technical and economic indicators, such as forward rates and macroeconomic variables outperform that of just using technical indicators alone? In addition, we extend the findings of earlier studies by Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) (on short-term government bonds) by studying the predictability of long-term government bond risk premia with maturities ranging from 17 to 20 years.

In this study, we use a total of 63 technical indicators. The first type of technical indicators is constructed based on moving averages of lagged forward spreads. Cochrane and Piazzesi (2005) provide strong empirical evidence that lagged forward rates contain information about excess bond returns beyond that contained in forward rates of current period. Their finding suggests that current term structure does not span all information relevant to the forecasting of future excess returns. Given this, we construct the first 48 technical indicators based on the moving averages of past forward spreads in the standard way of trend-following technical analysis.

Technical analysts frequently use volume data in conjunction with historical prices to identify market trends. In light of this, the second group of technical indicator for this study will be constructed based on "on-balance" volume (e.g., Granville, 1963). Since bond market trading volume data are unavailable to us, we construct the next 15 technical indicators based on stock market trading volume.[2] Hence, we have in total 63 technical indicators.

[1]In foreign exchange markets, academic studies generally find stronger support for the predictability of technical indicators. 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 professional currency mangers.

[2]Given that the stock and bond markets 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 stock market volume technical indicators can serve as a reasonable proxy for bond market volume indicators. We do not examine the technical indicators based on stock price moving averages as they are dominated by the same moving

Econometrically, including a large number of technical indicators in a predictive regression model simultaneously makes in-sample over-fitting a great concern. In doing so, it will likely result in poor out-of-sample forecasts.[3] To avoid over-fitting, following Ludvigson and Ng (2007, 2009, 2011), we generate bond risk premia forecasts based on a small number of principal component (PC) factors extracted from the set of 63 technical indicators.

We analyze the predictability for both in- and out-of-sample, because both approaches have their relative strengths. The use of the entire sample enables in-sample tests to be more powerful for detecting the existence of return predictability. In-sample estimation also provides more efficient parameter estimates and hence more precise estimates of the expected bond risk premium. On the other hand, out-of-sample methods implicitly test the stability of the data-generating process and guard against in-sample overfitting. Moreover, as emphasized by Goyal and Welch (2008), out-of-sample tests are clearly more relevant for investors.[4] Employing both in-sample and out-of-sample tests help to establish the robustness of our results.

In our in-sample analysis, we first examine the predictive ability of standalone technical indicators in a factor-augmented predictive regression framework. Then, we investigate whether these 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) studies, respectively. Our in-sample analysis shows that our set of technical indicators has stronger predictive power.

For 2- to 5-year short-term government bonds, over the sample period between January 1964 and December 2007, both CP_t and LN_t display strong forecasting power, with the R^2 range of 31–36% and 14–23%, respectively. Consistent with previous studies, the R^2 of CP_t falls to the range of 21–26% when the sample is extended to cover the December 2011 period (which includes the recent 2007–2009 financial crisis). In contrast, our set of technical indicators consistently generates high R^2 for both sample periods, with the values up to about 34%.

averages based on bond data.

[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) for a review on in-sample versus out-of-sample asset return predictability.

It is interesting to note that for the 17- to 20-year long-term government bonds, the in-sample R^2 of LN_t decreases significantly to about 5% over 1964:01 to 2007:12 period, but the R^2 of CP_t is still higher than 27%. To our surprise, the set of technical indicators constructed to predict the short-term bond risk premium, have R^2 of approximately 45% and 40% over the 1964:01–2007:12 and 1964:01–2011:12 periods, respectively, for all long-term maturities. These results are much higher than those of the short end of the term structure. When utilizing information from both technical indicators and economic variables, the results are stunning. Forecasts from the combination of technical and economic indicators perform the best, with R^2s up to 50% over the period 1964:01–2007:12, for both short- and long-term government bonds.

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 percentage reduction in the mean squared predictive error. Following methodology from many of the out-of-sample studies, we transform the technical factors into bond risk premia forecasts using a recursive predictive regression model. We calculate the R^2_{OS} statistics for the out-of-sample predictive regression forecasts based on technical indicator factors relative to historical average benchmark forecast. In the recursive procedure, at any time t, we implement the predictive regressions with all predictors, such as technical indicator factors, CP_t, and LN_t, using information available only up to t. This methodology avoids the look-ahead bias or the use of future information.

Our out-of-sample results corroborate that of the in-sample results. Similar to findings for the equity market, the bond market out-of-sample evidence is generally weaker than the in-sample results. For 2- to 5-year short-term government bonds, the forecasts based on CP_t have R^2_{OS}s up to 18% over the 1975:01–2007:12 out-of-sample evaluation periods. The R^2_{OS}s of CP_t further decline to about 3% over the longer 1975:01–2011:12 period.

In addition, 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. Similarly, the R^2_{OS}s of our technical indicators are lower than the corresponding in-sample ones. Nevertheless, our technical indicators still perform quite well over both the 1975:01–2007:12 and 1975:01–2011:12 out-of-sample periods, with the R^2_{OS} up to 26% and

22%, respectively. When all the predictors are combined together, the R^2_{OS}s improve substantially to about 33% during 1975:01–2007:12. For long-term bonds, the results qualitatively the same, with the R^2_{OS} range of 20–24%.

Statistically, both the in- and out-of-sample results are highly significant. The question that remains to be answered is, whether the statistical significance is of economic value for the investors. To assess the economic value of the out-of-sample bond risk premia forecasts, we follow the strategy outlined by Kandel and Stambaugh (1996) and Pástor and Stambaugh (2000) and many others. As with these studies, we examine the utility gains from an asset allocation perspective. To be more specific, we consider an investor who optimally allocates a portfolio between an n-year Treasury bond and one-year risk-free Treasury bill. We assume a mean-variance utility function for simplicity as in Campbell and Thompson (2008) and 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 our proposed predictors. The utility gain is calculated by comparing utility generated by our predictors versus one that is generated without any models. This method of calculation is similar to both the Zhu and Zhou (2009) and Neely, Rapach, Tu and Zhou (2011) studies, in the context of assessing the economic value of technical analysis. One way of looking at the utility gain is to think of it as the portfolio management fee that the investor would be willing to pay to have access to the predictive regression models. Another advantage of this approach is that it uses a utility function, which captures investor's risk aversion. Our methodology, which is to calculate investors utility gain addresses the criticism that many studies pertaining to profitability of technical indicators are ad hoc in nature.

As an example, suppose the risk aversion coefficient of an investor is three, then from our results, this investor will be willing to pay an annualized portfolio management fee up to 2.77%, over the time period 1975:01−2007:12, in order to have access to the 5-year government bond return forecast utilizing technical indicators. The fee can be as high as 3.06% when utilizing information contained in the combined technical and economic predictors. If the indicators were excluded, the fee drops to 0.69%. Over the extended 1975:01−2011:12 period, the fee for having access to 5-

year bond forecasts utilizing all the predictors falls to 2%. In this case, the importance of technical indicators becomes more apparent because without them, the fee would further drop to an economically undesirable level of -1.23%. For the 17- to 20-year long-term government bonds, the economic values are relatively large, about 3% for the 1985:01−2007:12 and 1985:01−2011:12 periods.

The economic value assessment is important as it sheds light on 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 equity market, as reported in a recent study by Neely, Rapach, Tu and Zhou (2011), the maximum monthly out-of-sample R^2_{OS} is 1.79%, and the maximum annual out-of-sample utility gain is 4.94%. Using this measure, it appears that the bond market is about 10 times more predictable than the stock market in terms of R^2_{OS}. But our economic value assessment reveals that the bond market is not 10 times more predictable than the stock market. This result suggests that across the financial markets, the economic value of forecasting is likely to be capped at similar levels. One possible reason could perhaps be due to arbitrage activities across various markets or inter-market efficiency.

Given the impressive predictive performance of our bond market technical indicators, a natural question one would ask is: Are there any theoretical reasons? A survey of past literature may provide some insights into the question. For example, Wachter (2006) shows that Campbell and Cochrane's (1999) habit-formation model can be adapted to explain time-varying bond risk premia. Brandt and Wang (2003) develop a model in which time-varying bond risk premia are driven by inflation as well as by aggregate consumption. Bansal and Shaliastovich (2010) provide an explanation on the predictability of bond risk premia based on long-run risks. In addition, in an economy when investors receive fundamental information at different times or process information at different speeds, Treynor and Ferguson (1985) show that technical analysis is valuable for assessing whether the information has been priced in. Hence trading will be more profitable when combining fundamentals with technicals than otherwise..

In a related study, Brown and Jennings (1989) argue that when investors receive fundamental information at the same time, but are heterogeneously informed, past price can help investors to make more precise inferences about their signals. Moreover, Grundy and McNichols (1989) and Blume, Easley, and O'Hara (1995) demonstrate that, as long as traders trade multiple rounds or they receive signals with differing quality, trading volume can provide useful information beyond prices. In a series of recent studies, Cespa and Vives (2012) and Guo and Xia (2012) show that, in a market with liquidity traders, prices can deviate from their fundamentals and technical analysis can be used to capture price trends.

Intuitively, technical indicators may capture information beyond that measured by the macroeconomic variables. This is because the set of the macroeconomic variables that are used in many studies are clearly not exhaustive, and they ignore important variables such as unexpected government policy changes and large shocks in the world economy.[5] However, any persistent reaction of the bond market to the latter variables may be captured by market technical indicators.

One can argue that technical indicators may be forward looking and perhaps be an effective tool in helping investor predict future events. For example, in the recent Fed QE3 exercise on January 13, 2012, prices of the long-term bond futures dropped 6 days out of 7, with one day virtually unchanged. The reason, as put forth by Aneiro in Barron's is, "Market had priced in expectations of some form of a third round of quantitative easing ahead of the Fed's policy-committee meeting."[6] This example illustrates that technical indicators may be forward looking and may capture market expectations of future macroeconomic data or events. In contrast, macroeconomic variables that are used in predictive regression studies emphasize the market impact of their realized values.

The predictability of stock market trading volume based technical indicators is potentially related to the negative correlation between stock and bond returns during periods of high uncertainty (e.g., Connolly, Stivers, and Sun, 2005; Beber, Brandt, and Kavajecz, 2009; Baele, Bekaert, and Inghelbrecht, 2010). It is suggested that bond returns tend to be high (low) relative to stock returns during days when stock trading volume and volatility increase (decrease) substantially. The nega-

[5]For example, Pástor and Veronesi (2012a, 2012b) point out that political news do impact asset prices, and they also find that uncertainty about political policy changes do raised the equity risk premia.

[6]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.

tive stock and bond return correlation is often referred to as the "flight to quality" and/or "flight to liquidity" effects. Theoretically, Vayanos (2004) shows that risk averse investment managers prefer liquid assets during volatile periods. Meanwhile, as their risk aversion also increases, it leads to higher risk premiums and resulting in driving down the prices of risky assets. Caballero and Krishnamurthy (2008) show that Knightian uncertainty may lead agents to shed risky assets in favor of safe assets when aggregate liquidity is low, thereby provoking a fight to quality. Brunnermeier and Pedersen (2009) show that margin requirements can trigger a liquidity spiral following a large bad shock, where liquidity deteriorates sharply for the high margin and volatile assets, leading to flight to quality or liquidity.

These research articles collectively provide a theoretical underpinning as to why our bond market technical indicators perform so well as predictors. It also lends support to the use of equity trading volume as a component in our forecasting models.

The rest of the paper is organized as follows. Section II 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. Section III reports the empirical results and Section IV concludes.

II. Econometric Methodology

This section describes our econometric framework, which includes the construction of technical indicators, as well as the estimation and evaluation of both in-sample and out-of-sample excess bond return. The forecasts are based on all the technical, financial and economic indicators.

A. Technical indicator construction

We follow Cochrane and Piazzesis (2005) 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 is a 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]

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

with

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

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 bond prices.[9] For example, recently when the n-year forward rates have 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 hence will generate 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 hence generating a buy signal. In Section III, 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

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

[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 $rx_{t+1}^{(2)},\ldots,rx_{t+1}^{(5)}$. The monthly sampling interval is then denoted as 1/12 of a year.

[9]Note that forward rates are transformed from log bond prices, thus the forward spread moving average technical indicators are functions of bond prices. We can also construct trading rules using the lagged excess bond returns, we leave these extensions for future research.

trends. In view of this, the second type of technical indicators are constructed based on "on-balance" volume (e.g., Granville, 1963). Since bond trading volume data (over the 1964 through 2011 period) are not available to us, we compute the volume indicator using stock market trading volume. Formally, we first define

$$OBV_t = \sum_{k=0}^{12t-1} VOL_{t-k/12} D_{t-k/12}, \tag{3}$$

where $VOL_{t-k/12}$ is a measure of the stock market trading volume between period $t-(k+1)/12$ and $t-k/12$ and $D_{t-k/12}$ is a binary variable that takes a value of 1 if $P_{t-k/12} - P_{t-(k+1)/12} \geq 0$ and -1 otherwise. We then form a trading volume-based buy or sell 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 hence generates a buy signal for bond market. The stock market trading volume based technical indicator might be related to flight to quality or flight to liquidity. In a situation with a high degree of uncertainty and risk aversion, bond returns tend to be higher relative to stock market returns and investors may shift their portfolios from a risky stock market towards safer 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 III, 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 that is at the heart of technical analysis. These are representative of the technical indicators that are often analyzed in the academic literature (e.g., Brock, Lakonishok, and LeBaron, 1992; Sullivan, Timmermann, and White, 1999). In this paper, we study whether technical indicators provide useful information in forecasting excess bond returns. Furthermore, we also aim to assess whether technical indicators could generate better excess bond return forecasts than those contained in 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) show that "real" and "inflation" factors are more important than the Cochrane and Pizzesis forward-rate factor when it comes to predictive power for excess bond returns on U.S. government bonds.

B. In-sample forecast

We use the standard predictive regression framework to analyze the in-sample predictive power of technical indicators for excess bond returns $rx_{t+1}^{(n)}$. However, analyzing the predictive power of a large number of potential technical predictors raises an important econometric issue. Including all of the potential regressors simultaneously in a multiple regression model can produce a very good in-sample fit, but it also can result in in-sample over-fitting. Hence, will likely leads to very poor out-of-sample forecasting performance. To be able to incorporate information from all of the technical indicators while avoiding over-fitting, we follow Ludvigson and Ngs (2007, 2009) recommendation and use a principle component approach. Let $x_t = (x_{1,t}, ..., x_{N,t})'$ denote the N-vector of potential technical predictors. Let $\hat{f}_t = (\hat{f}_{1,t}, ..., \hat{f}_{J,t})'$ represent 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 $\hat{f}_t$.[10] 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 subset 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 $rx_{t+1}^{(n)}$:

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

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

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

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

where Z_t includes economic predictors like CP_t and LN_t, which subsume the forecasting informa-

[10]BIC criterion is an asymptotic approximation to Bayesian posterior probabilities, and it asymptotically selects the best model with the most parsimonious parameterization among nested models (Schwarz, 1978). Nevertheless, we obtain similar results using alternative model selection criterion such as AIC.

tion in 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 that of economic predictors. Under the null hypothesis, β 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, β is different from zero, and the technical indicators are still useful in predicting excess bond returns even with the 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.

C. 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 to be a more relevant standard for assessing genuine return predictability in real time. 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 month of forecast formation, t.[11]

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

[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.

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

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

where $\tilde{\alpha}_t$ and $\tilde{\beta}_t$ are least squares estimates of α and β in (6) by regressing $\{rx_{t-k/12}^{(n)}\}_{k=0}^{12(t-1)-1}$ on a constant and $\{\tilde{F}_{t-1-k/12}\}_{k=0}^{12(t-1)-1}$. For each forecast formation period t, we first estimate the out-of-sample technical indicator PC factors $\{\tilde{f}_{t-k/12}\}_{k=0}^{12t-1}$ from a large number of potential individual technical indicators $\{x_{t-k/12}\}_{k=0}^{12t-1}$ using information available through period t. Then, the preferred subset of out-of-sample technical indicator factors $\{\tilde{F}_{t-k/12}\}_{k=0}^{12t-1}$ is selected from different subsets of $\{\tilde{f}_{t-k/12}\}_{k=0}^{12t-1}$ using the BIC criterion. Dividing the total sample of length T into m first period sub-sample and q second period sub-sample, where $T = m + q$, 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 out-of-sample evaluation periods: $\{\widetilde{rx}_{m+k/12}^{(n)}\}_{k=1}^{12q}$.[12]

Second, to analyze whether including technical indicators with economic variables could further improve the out-of-sample forecasting gains for excess bond returns, we generate an out-of-sample forecast of excess n-year 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:

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

where Z_t includes CP_t or LN_t. $\tilde{\alpha}_t$, $\tilde{\beta}_t$ and $\tilde{\eta}_t$ are least squares estimates of α, β and η in (7) from regressing $\{rx_{t-k/12}^{(n)}\}_{k=0}^{12(t-1)-1}$ on a constant, $\{\tilde{F}_{t-1-k/12}\}_{k=0}^{12(t-1)-1}$ and $\{Z_{t-1-k/12}\}_{k=0}^{12(t-1)-1}$, 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 out-of-sample evaluation periods: $\{\widetilde{rx}_{m+k/12}^{(n)}\}_{k=1}^{12q}$. In addition, to

[12]Observe that the forecasts are generated using a recursive (i.e., expanding) window for estimating α_t, β_t and η_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. Moreover, we obtain similar results using rolling estimation windows of various sizes.

assess the incremental forecasting power of technical indicators over economic variables, we also generate out-of-sample forecasts utilizing the information in the economic predictor Z_t alone:

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

where $\tilde{\alpha}_t$ and $\tilde{\eta}_t$ are least squares estimates based on information available through t.

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

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_{OS}^2 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,

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

where $rx_{m+k/12}^{(n)}$ represents the excess log return on n-year government bond from time $m-1+k/12$ to $m+k/12$, $\widetilde{rx}_{m+k/12}^{(n)}$ represents a competing out-of-sample forecast for $rx_{m+k/12}^{(n)}$ based on technical indicators or economic variables, and $\overline{rx}_{m+k/12}^{(n)}$ represents the historical average benchmark. Thus, when $R_{OS}^2 > 0$, the competing forecast outperforms the historical average benchmark in term of MSPE. We also 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 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; 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 compute utility gains for a mean-variance investor who optimally allocates across n-year government bond 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. Every month, the investor allocates between n-year government bond and 1-year risk-free bill. The investment decision is based on using an out-of-sample excess bond return forecast generated by a predictive regression model including technical indicators or economic variables as predictors versus a historical average forecast benchmark corresponding to the constant

[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.

expected excess bond return model. At the end of period t, the investor allocates

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

of his wealth to an n-year bond during period $t+1$, where γ is the coefficient of risk aversion, $\widetilde{rx}_{t+1}^{(n)}$ is a out-of-sample forecast for excess n-year bond return, and $\tilde{\sigma}_{n,t+1}^2$ 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 recent studies such as Campbell and Thompson (2008) and Thornton and Valente (2012), we constrain the portfolio weight on the n-year bond to lie between -1 and 4 to prevent extreme investments and limit the impact of estimation error.[15] 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 periods.

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

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

to the n-year Treasury bond during period $t+1$, where $\overline{rx}_{t+1}^{(n)}$ is the historical average forecast for

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

$rx_{t+1}^{(n)}$. The investor then realizes an average utility of

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

during the out-of-sample evaluation period, where $\bar{\mu}_n$ and $\bar{\sigma}_n^2$ are the sample mean and variance, respectively, for the the portfolio formed on Equation (14) using the sequence of historical average forecasts $\overline{rx}_{t+1}^{(n)}$. The utility gain is the difference between (13) and (15), $\hat{\nu}^{(n)} - \bar{\nu}^{(n)}$, 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).

III. 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. Results on the average utility gains from using technical indicators in forecasting excess bond returns are also reported in this section.

A. Data

We obtain the short-term zero coupon U.S. Treasury bond prices with maturities from one- through five-years from Fama-Bliss dataset available at the Center for Research in Securities Prices (CRSP) spanning the period 1964:01−2011:12. The long-term U.S. Treasury bond data with maturities from seventeen- to twenty-years are from the Federal Reserve's website, which provides updated data from Gürkaynak, Sack, and Wright (2007) beginning in 1981:07.[16] We compute the yields, forward rates, forward spreads, and annual log excess bond returns at a monthly frequency

[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).

as described in Section II. The macroeconomic fundamental data are obtained from Sydney C. Ludvigson's web page and used in Ludvigson and Ng (2009, 2011).[17] The macroeconomic dataset includes 132 monthly macroeconomic time series over the period 1964:01−2007:12. We use the monthly forward spreads when computing the forward spread moving average technical indicators 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 technical indicators in Equation (4).

Table 1 reports summary statistics for the first three 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 MA^{fs} and 15 trading volume technical indicators MA^{OBV}, respectively.[18] 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 2011:12. These in-sample PC factors are used to test the in-sample predictive power of technical indicators.[19]

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 68% of the total variation in the 48 MA^{fs} technical indicators, and the first three PC factors further increase the R_i^2 to 79%. Column R_i^2 of Table 1, Panel $\hat{f}_{i,t}^{OBV}$ presents that the first PC factor alone explains up to 83% of the total variation in the 15 MA^{OBV} technical indicators, and the first three

[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] We also conduct analysis on the out-of-sample predictive power of the technical indicators, 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 II.

[20] The first factor explains the largest fraction of the total variation in those technical indicators, and the ith factor explains the ith largest fraction of the total variation. The total variation is defined as the sum of the variance of the individual technical indicators. 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.

PC factors describe 93% of the total variation.

Column $AR1_i$ of Table 1 displays the first-order autoregressive coefficients of AR(1) model for each factor. Significant differences in persistence are found among PC factors. The autoregressive coefficients for forward spread moving average technical indicator PC factors $\hat{f}_t^{fs}$ are in the range of 0.88–0.97, and trading volume-based technical indicator PC factors $\hat{f}_t^{OBV}$ have autoregressive coefficients range of 0.01 to 0.93.[22]

Following Ludvigson and Ng (2009, 2011), we determine the preferred subset of technical indicator factors from all of the possible combinations of the estimated technical PC factors using short-term government bonds and following the 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, $\hat{\mathbf{F}}_t^{TI} = (\hat{F}_{1,t}^{fs}, \hat{F}_{3,t}^{fs}, \hat{F}_{1,t}^{OBV})$, are selected based on full sample information, where the 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 $\hat{\mathbf{F}}_t^{OBV} = \hat{F}_{1,t}^{OBV} \subset \hat{f}_t^{OBV}$.[23] In unreported results, we show that $\hat{F}_{1,t}^{fs}$ is a "level" forward spread moving average technical indicator factor with correlation of about 0.70 to 0.90 with the 48 individual forward spread moving average technical indicators; $\hat{F}_{3,t}^{fs}$ is a "slope" forward spread moving average technical indicator factor, which is positively correlated with the individual forward spread moving average technical indicators constructed on two- to four-year bonds but negatively correlated with the individual technical indicators constructed on five-year bond; and $\hat{F}_{1,t}^{OBV}$ is a "level" trading volume technical indicator factor with correlation of about 0.80 to 0.95 with the 15 individual trading volume technical indicators.[24]

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

[23]The same set of three technical indicator factors will be selected when controlling for CP_t and LN_t over the 1964:01−2007:12 period or controlling for CP_t alone over the 1964:01−2011:12 period.

[24]Note that the out-of-sample factors $\tilde{\mathbf{F}}_t^{fs}$, $\tilde{\mathbf{F}}_{t,t}^{OBV}$, and $\tilde{\mathbf{F}}_{t,t}^{TI}$ are determined recursively using data only available through forecast formation period t.

B. 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 period 1964:01−2007:12.[25] To examine the incremental predictive power of technical indicator factors beyond that contained in the financial and economic variables, we include CP_t and LN_t, which are the Cochrane and Piazzesi (2005) factor and Ludvigson and Ng (2009) factor, respectively, as conditioning variables. We report in-sample forecasting results of using CP_t or LN_t alone as forecast benchmark. Table 3 reports for the period of 1964:01−2011:12, which includes the recent 2007–2009 financial crisis and later periods. Since the macroeconomic dataset of Ludvigson and Ng (2009) is only available up to December 2007, we hence only control for CP_t alone over the latter sample period. Following Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009), the standard error of the regression coefficients are corrected for serial correlation using the Newey and West (1987) techniques with 18 lags. We use 18 lags because the annual log excess bond returns have an MA(12) error structure that are induced by overlapping observations.

According to Row 1 of the top panel of Table 2, consistent with Cochrane and Piazzesi (2005), the forward rate factor CP_t generates huge in-sample forecasting power for excess returns on two-year government bond, $rx_{t+1}^{(2)}$, over the 1964:01−2007:12 period, with adjusted R^2 of 31%. In addition, Row 2 of the top panel of Table 2 presents that the macroeconomic variable factor LN_t produces sizable in-sample adjusted R^2 of 23% over the 1964:01−2007:12 period. In his website, John Cochrane suggests that the predictive power of CP_t seems to be weak during the recent 2007−2009 financial crisis. Consistent with his finding, Row 1 of the top panel of Table 3 shows that the R^2 of CP_t is only of 21% over the 1964:01−2011:12 period.[26]

Next, Rows 3−5 of the top panel of Table 2 show that technical indicator factors have sizable in-sample forecasting power over the 1964:01−2007:12 period, which is comparable to that of

[25] We find similar results for simple raw excess returns.

[26] Recent studies such as Duffee (2012) and Thornton and Valente (2012) also find similar results.

economic variables CP_t and LN_t in term of R^2. The two forward spread moving average technical indicator factors, $\hat{\mathbf{F}}_t^{fs} = (\hat{F}_{1,t}^{fs}, \hat{F}_{3,t}^{fs})$, explain 28% of the two-year excess bond return variation; and both $\hat{F}_{1,t}^{fs}$ and $\hat{F}_{3,t}^{fs}$, which are the first and third PC factors estimated from 48 forward spread moving average trading signals, are statistically significant at the 1% or better level. In addition, the trading volume technical indicator factor, $\hat{\mathbf{F}}_t^{OBV} = \hat{F}_{1,t}^{OBV}$, produces adjusted R^2 of 10%, with statistical significance for $\hat{F}_{1,t}^{OBV}$, the first PC factor estimated from 15 trading volume technical indicators. Row 5 of Table 2 further shows that $\hat{\mathbf{F}}_t^{TI}$, which combines information from $\hat{\mathbf{F}}_t^{fs}$ and $\hat{\mathbf{F}}_t^{OBV}$ together, generates highest adjusted R^2 of 32%, with all technical factors statistically significant at the conventional level.[27]

Rows 2−4 of the top panel of Table 3 report the in-sample forecasting results of technical indicator factors for $rx_{t+1}^{(2)}$ over the 1964:01−2011:12 period. In contrast to CP_t, for this longer sample period, technical indicator factors generate consistently strong forecasting power with R^2 of 30%; all of the three technical indicator factors are statistically significant at conventional level.

When combining information in technical indicators and economic variables including $\hat{\mathbf{F}}_t^{TI}$, CP_t, and LN_t together, the predictive regression forecasts perform the best. The forecasts remarkably outperform the corresponding forecasts based on economic variables or technical indicators alone, and generate the highest in-sample R^2 of 47% during 1964:01−2007:12 period, as shown in Row 6 of Panel $rx_{t+1}^{(2)}$ of Table 2. All three technical indicator factors are statistically significant at reasonable level. For the 1964:01−2011:12 sample period, the same conclusion holds qualitatively. For example, Row 5 of Panel $rx_{t+1}^{(2)}$ of Table 3 shows that forecasts based on $\hat{\mathbf{F}}_t^{TI}$ and CP_t together outperform the forecasts based on either alone, too. Following Ludvigson and Ng (2009), we find that all three technical indicator factors are relatively economically important by inspecting the absolute value of regression coefficients. In summary, our findings suggest that technical indicators contain additional forecasting information beyond that contained in forward rates, yields, and macroeconomic variables.

The remaining three panels of Tables 2 and 3 show that both the forward spread moving

[27] Following Cochrane and Piazzesi (2005), we find that a single-factor predictor which is a single linear combination of the three technical indicator factors in $\hat{\mathbf{F}}_t^{TI}$ contains almost the same predictive power.

average-based and trading volume-based technical indicator factors have strong in-sample forecasting power for excess returns on shot-term government bonds with maturities of three, four, and five years over both the 1964:01−2007:12 and 1964:01−2011:12 sample periods. The three technical indicator factors in $\hat{\mathbf{F}}_t^{TI}$ generate high R^2 up to 34%. Moreover, the predictive power of technical indicators remains significant for each short-term government bond in the presence of economic predictors CP_t and LN_t. For example, in Table 2, combining the technical indicator factor $\hat{\mathbf{F}}_t^{TI}$ with CP_t and LN_t will increase the R^2 to 47% for the five-year bond excess returns. In summary, our results show that both the technical indicators and economic variables contain significant forecasting information for excess returns of short-term government bonds. Hence, fixed income investors should use both technical indicators and economic variables together in forecasting excess returns on short-term government bonds.

As discussed earlier, most of the current literature on bond risk premia predictability focus on short-term government bonds with maturities of 2 to 5 years. Complimenting earlier studies like Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009), this paper also studies the predictability of excess returns on long-term government bonds. Tables 3 and 4 summarizes the results for the sample period from 1981:07 to 2007:12 and 1981:07 to 2011:12, respectively. The sample is relatively shorter due to data availability.

Table 4 shows that CP_t generates a sizable R^2 of 27–28% for excess returns on long-term government bonds with maturities ranging from 17 to 20 years over 1981:07–2007:12 period.[28] Over the longer period 1981:07–2011:12, the R^2 of CP_t reduce to 19–20% in Table 5, confirming the deterioration of predictability of CP_t during the recent periods. Nonetheless, CP_t contains large forecasting power for both short-term and long-term government bonds.

Strikingly, the predictability of LN_t diminishes sharply for long-term government bonds. According to Rows 2 of Table 4, the R^2 of LN_t reduces to about only 5% for the 17- to 20-year long maturity government bonds, significantly smaller than the corresponding values for the sample of

[28] Due to space constraint, we only reports results for 17- to 20-year long-term government bonds. In unreported results, we find that the predictability of middle-term bonds like 10-year bond is in the middle of that of short-term and long-term government bonds.

short-term government bonds in Table 2. In unreported results, we find that none of the macroeconomic factors in LN_t are statistically significant over 1981:07–2007:12 period. This finding suggests that while LN_t is useful in forecasting short-term government bonds, it has little predictability for excess returns on long-term government bonds.

However, the selected technical indicators factor $\hat{\mathbf{F}}_t^{TI}$ to best predict the short-term bond risk premium, has a much higher R^2 when we apply it to the long-term government bond sample.[29] We document a high R^2 value of 45% for all the long-term maturities over 1981:07–2007:12 period (see Rows 5 of Table 4). Hence, to predict long-term bond risk premia, $\hat{\mathbf{F}}_t^{TI}$ is substantially more powerful than economic variables such as CP_t and LN_t. In addition, the predictability of $\hat{\mathbf{F}}_t^{TI}$ remains strong over the longer period 1981:07–2011:12, with sizable R^2 of 40%, as reported in Rows 4 of Table 5.

Again, when we combine information in $\hat{\mathbf{F}}_t^{TI}$, CP_t, and LN_t together, the predictive regression models perform the best in predicting excess long-term bond returns. But, the improvement in forecasting power is less salient than that for short-term government bonds, with the R^2 of about 48% and 42% over the 1981:07–2007:12 and 1981:07–2011:12 periods, respectively. $\hat{\mathbf{F}}_t^{TI}$ thus plays a bigger role relative to CP_t and LN_t in predicting long-term government bonds. It is interesting to note that, of the three technical indicator factors in $\hat{\mathbf{F}}_t^{TI}$, the two forward spread moving average technical indicator factors, $\hat{F}_{1,t}^{fs}$ and $\hat{F}_{3,t}^{fs}$, are particularly useful. Regression coefficients on these two factors are economically large in absolute value, and statistically significant at about 1% level for all the long-term government bonds.

C. R_{OS}^2 statistics

Tables 6 and 7 reports the Campbell and Thompson (2008) out-of-sample R_{OS}^2 statistics for out-of-sample excess return forecasts on 2- to 5-year short-term government bonds over the 1975:01–2007:12 and 1975:01–2011:12 evaluation periods, respectively. R_{OS}^2 statistics measure the reduc-

[29]Note that, similar to CP_t, 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.

tion in mean square prediction error (MSPE) for the excess bond return forecasts based on technical indicators and economic variables relative to the historical average benchmark forecast. We use the 1964:01−1974:01 as the initial in-sample period when forming the first out-of-sample forecast of excess log annual bond return for 1975:01. 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.

Recall that our technical indicator factors $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ are determined recursively from PC factors estimated from 48 forward spread moving average technical indicators and 15 trading volume technical indicators according to the BIC criterion, respectively; $\tilde{\mathbf{F}}_t^{TI} = (\tilde{\mathbf{F}}_t^{fs}, \tilde{\mathbf{F}}_t^{OBV})$ includes information from both the forward spread and trading volume technical indicators. To assess the additional forecasting power of technical indicators, we also generate out-of-sample forecasts with economic variables CP_t and LN_t, where CP_t and LN_t are estimated recursively as well. All regression parameters in the predictive regression models are also estimated recursively using only the information available through period of forecast formation t.

The third column of Table 6 shows that CP_t produces large positive R^2_{OS} statistics relative to the historical average benchmark for excess returns on the 2- to 5-year short-term government bonds over the 1975:01–2007:12 evaluation period. Similar to the previous literature, R^2_{OS} statistics are generally smaller than the in-sample ones. However, all of the R^2_{OS} are still non-trivial economically, in the range of 15.2–17.9%, and statistically significant at 5% level. In contrast, LN_t generates sharply smaller R^2_{OS} statistics over the same evaluation period. They are 4.7%, 0.1%, -1.4%, and -4.2% for two- to five-year government bonds, respectively (see the fifth column of Table 6). Only the one for the two-year bond is economically large (4.7%) and statistically significant.

The second column of Table 7 provides out-of-sample evidence on the deterioration of the predictability of CP_t over the recent sample period. Consistent with our in-sample findings, although CP_t is still a significant out-of-sample predictor over the longer 1975:01–2011:12 evaluation period, the R^2_{OS} is sharply reduced to the range of 2.3–3.8% for 2- to 5-year government bonds.

Turning to technical indicators, $\tilde{\mathbf{F}}_t^{TI}$ and its two constituting components $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ consistently produce large positive out-of-sample forecasting gains for 2- to 5-year short-term government bond excess returns $rx_{t+1}^{(n)}$. Over the 1975:01–2007:12 evaluation period, the R_{OS}^2 of $\tilde{\mathbf{F}}_t^{fs}$ improve monotonically from 22.9% to 25.2% in the second column of Panel A of Table 6, as bond maturities increase from 2 years to 5 years. $\tilde{\mathbf{F}}_t^{OBV}$ also produces positive R_{OS}^2 for short-term government bonds in the second column of Panel B of Table 6, ranging from 5.1% ($n = 5$) to 7.9% ($n = 2$). The second column of Panel C of Table 6 shows that $\tilde{\mathbf{F}}_t^{TI}$ can further improve forecasts based on $\tilde{\mathbf{F}}_t^{fs}$ or $\tilde{\mathbf{F}}_t^{OBV}$ alone; the R_{OS}^2 statistics are about 26% for 2- to 5-year government bonds, and all of them are statistically significant at the 1% level.

More importantly, in contrast to CP_t, the out-of-sample predictability of technical indicator factors $\tilde{\mathbf{F}}_t^{TI}$, $\tilde{\mathbf{F}}_t^{fs}$, and $\tilde{\mathbf{F}}_t^{OBV}$ remains economically and statistically significant for 2- to 5-year short-term government bonds over the longer 1975:01–2011:12 evaluation period. For example, $\tilde{\mathbf{F}}_t^{TI}$ produces sizable R_{OS}^2 up to 22.3% in the seventh column of Table 7, with statistical significance at 1% level.

Previous studies such as Neely, Rapach, Tu and Zhou (2011) show that equity risk premium forecasts utilizing information from both technical indicators and economic variables substantially improve forecasting performance relative to just using economic variables alone. We show that the results of short-term government bonds are similar to those of the equity market; short-term bond risk premia forecasts combining technical indicators such as $\tilde{\mathbf{F}}_t^{TI}$, $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$ with economic variables like CP_t and LN_t can almost always outperform forecasts based on economic variables alone. For example, over the 1975:01–2007:12 out-of-sample evaluation period, forecasts based on the combination of $\tilde{\mathbf{F}}_t^{TI}$, CP_t and LN_t perform the best and sharply improve the R_{OS}^2 to the range of 30.7–33.2% for 2- to 5-year government bonds in the last column of Panel C of Table 6, which is about two times larger than the corresponding R_{OS}^2 range based on CP_t and LN_t alone in the seventh column of Panel C. Over the longer 1975:01–2011:12 period, the R_{OS}^2 statistics of adding $\tilde{\mathbf{F}}_t^{TI}$ with CP_t range from 19.8% to 21.3% in the last column of Table 7. Nevertheless, the technical indicators are still very important. Without them, the R_{OS}^2 would drop to an economically low range of 2.3–3.8% (see the first column of Table 7).

Next, we examine the out-of-sample predictability of excess returns on long-term government bonds with maturities from 17 to 20 years.[30] Tables 8 and 9 report the R^2_{OS} statistics of long-term government bonds over the 1985:01–2007:12 and 1985:01–2011:12 evaluation periods, respectively. Data availability limits the starting date for the 17- to 20-year government bonds to 1981:07, as such, we use the 1981:07−1984:01 as the initial in-sample period to forecast the log annual excess return for 1985:01.

The third column of Tables 8 shows that CP_t has R^2_{OS} of about 24% for 17- to 20-year long-term government bonds over the 1985:01–2007:12 period. All the R^2_{OS} are economically large and statistically significant at 1% level. More importantly, different from short-term government bonds, CP_t remains useful for long-term government bonds over the longer 1985:01–2011:12 period in the second column of Tables 9, with R^2_{OS} ranging from 13.1–15.1%. Hence, while CP_t's forecasting power for short-term government bonds has diminished during the recent sample periods, its forecasting power for long-term bonds is higher and remains robust to including the recent sample periods.

The fifth column of Table 8 shows that LN_t has poor forecasting performance for 17- to 20-year government bonds.[31] All the R^2_{OS} statistics are negative with large absolute values, indicating the historical average sharply outperforms LN_t in forecasting long-term government bonds in terms of MSPE.

Consistent with the in-sample results reported earlier, the second column of Table 8, Panel A shows that $\tilde{\mathbf{F}}_t^{fs}$ has strong forecasting power for long-term government bonds over the 1985:01–2007:12 period in term of R^2_{OS}.[32] The R^2_{OS} statistics are in the range of 39.4% to 44.0% for 17- to 20-year government bonds, remarkably larger than the 25.6–33.9% range for 2- to 5-year government bonds. In addition, the out-of-sample forecasting power of $\tilde{\mathbf{F}}_t^{fs}$ is robust for including recent sample periods. The third column of Table 9 shows that $\tilde{\mathbf{F}}_t^{fs}$ generates R^2_{OS} up to 37.5% for 17-

[30]Note that out-of-sample forecasting results for mid-term government bonds are in the middle of short-term and long-term government bonds.

[31]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.

[32]Note that we use the model $\tilde{\mathbf{F}}_t^{fs}$ that produces the best prediction for the short-term government bonds sample on the long term government bonds sample.

to 20-year government bonds over the 1985:01–2011:12 period. 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 long-term government bond returns. Nevertheless, $\tilde{\mathbf{F}}_t^{TI}$, which incorporates information in both $\tilde{\mathbf{F}}_t^{fs}$ and $\tilde{\mathbf{F}}_t^{OBV}$, consistently produces large positive R_{OS}^2 of about 20% for long-term government bonds during both sample periods.

Tables 8 and 9 also show that 17- to 20-year government bond return forecasts combining $\tilde{\mathbf{F}}_t^{TI}$ together with CP_t and LN_t almost always substantially outperform the corresponding forecasts based on CP_t and LN_t alone. The improvement can be even larger when combining $\tilde{\mathbf{F}}_t^{fs}$ rather than $\tilde{\mathbf{F}}_t^{TI}$ with the economic variables, indicating that technical indicators provide substantial additional forecasting information for long-term government bonds.

D. Asset Allocation

Table 10 reports the economic value of various bond risk premia forecasts for a mean-variance investor with risk aversion coefficient of three. We assume that the investor optimally allocates a portfolio between one-year risk-free Treasury bill and n-year Treasury bond using out-of-sample n-year simple excess bond return forecasts generated from part or all of the technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ and economic variables CP_t and LN_t. Panels A and B report the average utility gains, in annualized percent, for the portfolios constructed with various forecasting models on 2- to 5-year short-term government bonds over the 1975:01−2007:12 and 1975:01−2011:12 out-of-sample evaluation periods, respectively; Panels C and D report the utility gains for the portfolios constructed on 17- to 20-year long-term government bonds over the 1985:01−2007:12 and 1985:01−2011:12 periods, respectively. The average utility gain is the portfolio management fee that an investor would be willing to pay to have access to the bond risk premia forecast vis-á-vis the historical average forecast benchmark which ignores the predictability in bond risk premia.

Recent studies like Thornton and Valente (2012) suggest that while CP_t generates huge R^2, it can be of little economic value for the investor. Reminiscent of Thornton and Valente (2012), CP_t displays very limited economic value for 2- to 5-year short-term government bonds in the third column of Panels A and B. Although CP_t produces positive utility gains for all the four short-term government bonds over the period 1975:01−2007:12, none of which is economically meaningful, with the maximum of 0.45% per annum only. The performance of portfolios formed on CP_t becomes negative over the longer 1975:01−2011:12 period, with the utility gains ranging from −0.37% to −1.23% per annum. Therefore, a simple short-term government bond portfolio strategy based on the historical average forecast can outperform portfolios constructed on CP_t over the 1975:01−2011:12 period. In addition, according to the fifth column of Panel A, all the four utility gains of LN_t are negative over 1975:01−2007:12; LN_t thus also fails to generate positive economic value for short-term government bonds.

The second column of Panels A and B elucidates that, for short-term government bonds, the economic value of $\tilde{\mathbf{F}}_t^{TI}$ is substantially higher than that obtained using CP_t and LN_t. Over the 1975:01−2007:12 period, the annualized utility gains of $\tilde{\mathbf{F}}_t^{TI}$ increase monotonically from 0.71% for 2-year government bond to 2.77% for 5-year government bond. The implication is that the investor would be willing to pay an annual management fee more than 2.5% to have access to the excess bond return forecasts generated from $\tilde{\mathbf{F}}_t^{TI}$. It is interesting to note that the utility gains of $\tilde{\mathbf{F}}_t^{TI}$ remain positive and economically large over the longer 1975:01−2011:12 period, during which CP_t underperforms the historical average benchmark. Overall, technical indicators seem to perform better than economic variables in forecasting short-term government bonds under the more realistic asset allocation approach.

We then study the economic gains to using information in technical indicators and economic variables in conjunction in forecasting short-term government bonds. A forecasting model based on CP_t, LN_t, and $\tilde{\mathbf{F}}_t^{TI}$ generates utility gains up to 3.06% per annum for short-term government bonds in the eighth column of Panel A, which easily exceed all the corresponding utility gains based on CP_t and LN_t in the seventh column of Panels A and B over the 1975:01−2007:12 sample period. The fourth (sixth) column of Panels A and B further shows that adding $\tilde{\mathbf{F}}_t^{TI}$ with CP_t (LN_t) always generates remarkably higher utility gains than forecasts based on CP_t (LN_t) alone in the third (fifth) column. For example, over the 1975:01−2011:12 sample period, although

CP_t has negative utility gains for 2- to 5-year short-term government bonds, all the utility gains of combining $\tilde{\mathbf{F}}_t^{TI}$ with CP_t are positive, reaching a maximum of 1.95% per annum. The asset allocation results thus confirm the previous forecasting results based on in- and out-of-sample R^2: technical indicators capture additional information relevant for forecasting the short-term bond risk premia.

Next, we focus on the utility gains on long-term government bonds in Panels C and D of Table 10. The third column of Panel C shows that CP_t has economically large utility gains up to 2.83% per annum for 17- to 20-year long-term government bonds over the 1985:01−2007:12 period. The gains again fall sharply to the range of 0.38–0.54% per annum over the longer 1985:01−2011:12 period in the third column of Panel D. In contrast, all the utility gains of LN_t are negative for 17- to 20-year government bonds.

The second column of Panel C presents that the utility gains of $\tilde{\mathbf{F}}_t^{TI}$ range from 2.07% to 3.73% per annum for 17- to 20-year long-term government bonds over the 1985:01−2007:12 period. $\tilde{\mathbf{F}}_t^{TI}$ also produces high utility gains up to 2.81% per annum over the 1985:01−2011:12 period in second column of Panel D. These findings indicate that $\tilde{\mathbf{F}}_t^{TI}$ is at least as useful as CP_t in forecasting long-term government bonds. In addition, the utility gains of combining $\tilde{\mathbf{F}}_t^{TI}$ with CP_t or LN_t are almost always higher than those based on CP_t or LN_t alone in Panels C and D, which demonstrates the incremental economic value of technical indicators in forecasting long-term government bond premia relative to economic variables.

Overall, Table 10 shows that, while CP_t generates fairly sizable economic value over sample period up to 2007:12, particularly for long-term government bonds, its performance falls remarkably over the extended sample period to 2011:12; LN_t always fails to produce any economic value for either short- or long-term government bonds. In contrast, technical indicator factor $\tilde{\mathbf{F}}_t^{TI}$ displays consistently large economic value for both short- and long-term bonds and over various sample sample periods. In addition, forecasts adding $\tilde{\mathbf{F}}_t^{TI}$ with economic variables CP_t and LN_t almost always generate higher utility gains than forecasts based on economic variables alone.

IV. Conclusion

In this paper, we study the predictability of technical indicators for U.S. government bond risk premia, filling a gap in the literature that largely ignores this important piece of information that is widely employed by traders and investors. We find that technical indicators have economically and statistically significant forecasting power both in- and out-of-sample, and for both short- and long-term government bonds. The novelty of our results is that we show technical indicators are more useful than economic variables that are used in many of the recent academic studies on excess bond return predictability. Moreover, a forecasting model that combines information in technical indicators together with economic variables substantially outperforms forecasts based on models using economic variables only. From an asset allocation perspective, our results show that forecasts using all the information consistently generate sizable economic gains. Our findings are robust for short- and long-term bonds over different sample periods. Whereas forecasts based on purely economic variables alone invariably deliver lower economic values or even losses.

In addition, this paper sheds some light to the understanding of the puzzle that the bond market are much more predictable than the stock market in term of R^2. Our results show that while the bond market is about 10 times more predictable than the stock market in terms of out-of-sample R^2, the economic value accruing to bond market predictability is not 10 times more profitable than the stock market, in fact, the two values are rather close. This suggests that across the various financial markets, economic value of forecasting is likely to be the same due to cross market arbitrage or intermarket efficiency.

Many recent studies such as Dai and Singleton (2002), Duffee (2002, 2006, 2011), Ang and Piazzesi (2003), Diebold and Li (2006), Diebold, Rudebusch, and Aruoba (2006), Moench (2008), Joslin, Priebsch, and Singleton (2010), Joslin, Singleton, and Zhu (2011), and Wright (2011), among others, incorporate economic variables into term structure modelling. The main contribution of these models is that they help shed insights on the predictability of the economic variables in the bond market. However, none of the models take into account the relevant information in technical indicators that are widely watched and used by traders and investors. Hence, a challenge to financial economists is to develop theories that will incorporate both fundamental and technical indicators in term-structure models of bond pricing.

Reference

Allen, F., and R. Karjalainen. “Using Genetic Algorithms to Find Technical Trading Rules.” *Journal of Financial Economics*, 51 (1999), 245–271.

Ang, A., and M. Piazzesi. “A No-Arbitrage Vector Autoregression of Term Structure Dynamics with Macroeconomic and Latent Variables.” *Journal of Monetary Economics*, 50 (2003), 745–787.

Baele, L.; G. Bekaert; and K. Inghelbrecht. “The Determinants of Stock and Bond Return Comovements.” *Review of Financial Studies*, 23 (2010), 2374–2428.

Bai, J., and S. Ng. “Determining the Number of Factors in Approximate Factor Models.” *Econometrica*, 70 (2002), 191–221.

Bansal, R., and A. Yaron. “Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles.” *Journal of Finance*, 59 (2004), 1481–1509.

Bansal, R., and I. Shaliastovich. “A Long-Run Risks Explanation of Predictability Puzzles in Bond and Currency Markets.” Working Paper, Duke University (2010).

Beber, A.; M. W. Brandt; and K. A. Kavajecz. “Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market.” *Review of Financial Studies*, 22 (2009), 925–957.

Bekaert, G., and E. Engstrom. “Inflation and the Stock Market: Understanding the “Fed Model”.” *Journal of Monetary Economics*, 57 (2010), 278-294.

Bessembinder, H., and K. Chan. “Market Efficiency and the Returns to Technical Analysis.” *Financial Management*, 27 (1998), 5–17.

Billingsley, R. S., and D. M. Chance. “The Benefits and Limits of Diversification among Commodity Trading Advisors.” *Journal of Portfolios Management*, 23 (1996), 65–80.

Blume, L.; D. Easley; and M. O’hara. “Market Statistics and Technical Analysis: The Role of Volume.” *Journal of Finance*, 49 (1994), 153–181.

Brandt, M. W., and K. Q. Wang. “Time-Varying Risk Aversion and Unexpected Inflation.” *Journal of Monetary Economics*, 50 (2003), 1457–1498.

Brock, W.; J. Lakonishok; and B. LeBaron. “Simple Technical Trading Rules and the Stochastic Properties of Stock Returns.” *Journal of Finance*, 47 (1992), 1731–1764.

Brown, S. J.; W. N. Goetzmann; and A. Kumar. “William Peter Hamilton’s Track Record Reconsidered.” *Journal of Finance*, 53 (1998), 1311–1333.

Brown, D. P., and R. H. Jennings. “On Technical Analysis.” *Review of Financial Studies*, 2 (1989), 527–551.

Brunnermeier, M. K., and L. H. Pedersen. “Market Liquidity and Funding Liquidity.” *Review of Financial Studies*, 22 (2009), 2201–2238.

Campbell, J. Y., and J. H. Cochrane. "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior." *Journal of Political Economy*, 107 (1999), 205–251.

Campbell, J. Y., and R. J. Shiller. "Yield Spreads and Interest Rates: A Bird's Eye View." *Review of Economic Studies*, 58 (1991), 495–514.

Campbell, J. Y., and S. B. Thompson. "Predicting the Equity Premium Out of Sample: Can Anything Beat the Historical Average?" *Review of Financial Studies*, 21 (2008), 1509–1531.

Campbell, J. Y., and T. Vuolteenaho. "Inflation Illusion and Stock Prices." *American Economic Review*, 94 (2004), 19-23.

Cespa, G., X. Vives. "Dynamic Trading and Asset Prices: Keynes vs. Hayek." *Review of Economic Studies*, 79 (2012), 539–580.

Clark, T. E., and M. W. McCracken. "Tests of Equal Forecast Accuracy and Encompassing for Nested Models." *Journal of Econometrics*, 105 (2001), 85–110.

Clark, T. E., and M. W. McCracken. "Improving Forecast Accuracy by Combining Recursive and Rolling Forecasts." *International Economic Review*, 50 (2009), 363–395.

Clark, T. E., and K. D. West. "Approximately Normal Tests for Equal Predictive Accuracy in Nested Models." *Journal of Econometrics*, 138 (2007), 291–311.

Caballero, R. J., and A. Krishnamurthy. "Collective Risk Management in a Flight to Quality Episode." *Journal of Finance*, 63 (2008), 2195–2230.

Cochrane, J. H., and M. Piazzesi. "Bond Risk Premia." *American Economic Review*, 95 (2005), 138–160.

Cochrane, J. H., and M. Piazzesi. "Decomposing the Yield Curve." Working Paper, University of Chicago (2008).

Connolly, R.; C. Stivers; and L. Sun. "Stock Market Uncertainty and the Stock-Bond Return Relation." *Journal of Financial and Quantitative Analysis*, 40 (2005), 161–195.

Connor, G., and R. Korajczyk. "Performance Measurement with the Arbitrage Pricing Theory: A New Framework for Analysis." *Journal of Financial Economics*, 15 (1986), 373–394.

Connor, G., and R. Korajczyk. "Risk and Return in Equilibrium APT: Application of a New Test Methodology." *Journal of Financial Economics*, 21 (1988), 255–289.

Covel, M. *Trend Following: How great Traders Make Millions in Up or Down Markets*. New York: Prentice–Hall (2005).

Cowles, A. "Can Stock Market Forecasters Forecast?" *Econometrica*, 1 (1933), 309–324.

Dai, Q., and K. Singleton. "Expectation Puzzles, Time-Varying Risk Premia, and Affine Models of the Term Structure." *Journal of Financial Economics*, 63 (2002), 415–441.

Della Corte, P.; L. Sarno; and D.L. Thornton. "The Expectations Hypothesis of the Term Structure of Very Short-term Rates: Statistical Tests and Economic Value." *Journal of Financial Economics*, 89 (2008), 158–174.

Diebold, F. X., and C. Li. "Forecasting the Term Structure of Government Bond Yields." *Journal of Econometrics*, 127 (2006), 337–364.

Diebold, F. X., and R. S. Mariano. "Comparing Predictive Accuracy." *Journal of Business and Economic Statistics*, 13 (1995), 253–263.

Diebold, F. X.; G. D. Rudebusch; and S. B. Aruoba. "The Macroeconomy and The Yield Curve: A Dynamic Latent Factor Approach." *Journal of Econometrics*, 131 (2006), 309–338.

Duffee, G. R. "Term Premia and Interest Rate Forecasts in Affine Models." *Journal of Finance*, 5 (2002), 405–443.

Duffee, G. R. "Term Structure Estimation Without Using Latent Factors." *Journal of Financial Economics*, 79 (2006), 507–536.

Duffee, G. R. "Information in (and not in) the Term Structure." *Review of Financial Studies*, 24 (2011), 2895–2934.

Duffee, G. R. "Forecasting Interest Rates." In A. Timmermann, and G. Elliott (eds.), *Handbook of Economic Forecasting*, forthcoming. Amsterdam: Elsevier Science B.V. (2012).

Fama, E. F., and R. H. Bliss. "The Information in Long-Maturity Forward Rates." *American Economic Review*, 77 (1987), 680–692.

Fama, E. F., and M. Blume. "Filter Rules and Stock Market Trading." *Journal of Business*, 39 (1966), 226–241.

Fama, E. F., and K. R. French. "Business Conditions and Expected Returns on Stocks and Bonds." *Journal of Financial Economics*, 25 (1989), 23–49.

Goyal, A., and I. Welch. "A Comprehensive Look at the Empirical Performance of Equity Premium Prediction." *Review of Financial Studies*, 21 (2008), 1455–1508.

Goyenko, R. Y., and A. D. Ukhov. "Stock and Bond Market Liquidity: A Long-Run Empirical Analysis." *Journal of Financial and Quantitative Analysis*, 44 (2009), 189–212.

Grundy, B. D., and M. McNichols. "Trade and the Revelation of Information through Prices and Direct Disclosure." *Review of financial Studies*, 2 (1989), 495–526.

Guo, M., and C. Xia. "Technical Trading and Strategic Liquidity Provision." Working Paper, Hong Kong University of Science and Technology (2012).

Gürkaynak, R. S.; B. Sack; and J. H. Wright. "The U.S. Treasury Yield Curve: 1961 to the Present." *Journal of Monetary Economics*, 54 (2007), 2291–2304.

Han, Y.; K. Yang; and G. Zhou. "A New Anomaly: The Cross-Sectional Profitability of Technical Analysis." *Journal of Financial and Quantitative Analysis*, forthcoming (2012).

Hansen, P. "A Winner's Curse for Econometric Models: On the Joint Distribution of In-Sample Fit and Out-of-Sample Fit and its Implications for Model Selection." Working Paper, Stanford University (2009).

Ilmanen, A. "Time Varying Expected Bond Returns in International Bond Markets." *Journal of Finance*, 50 (1995), 481–506.

Jensen, M. C., and G. A. Benington. "Random Walks and Technical Theories: Some Additional Evidence." *Journal of Finance*, 25 (1970), 469–482.

Joslin, S.; M. Priebsch; and K. Singleton. "Risk Premiums in Dynamic Term Structure Models with Unspanned Macro Risks." Working Paper, Stanford University (2010).

Joslin, S.; K. Singleton; and H. Zhu. "A New Perspective on Gaussian Dynamic Term Structure Models." *Review of Financial Studies*, 24 (2011), 926–970.

Kandel, S., and R. F. Stambaugh. "On the Predictability of Stock Returns: An Asset Allocation Perspective." *Journal of Finance*, 51 (1996), 385–424.

Keim, D. B., and R. F. Stambaugh. "Predicting Returns in the Stock and Bond Markets." *Journal of Financial Economics*, 17 (1986), 357–390.

Lander, J.; A. Orphanides; and M. Douvogiannis. "Earnings Forecasts and the Predictability of Stock Returns: Evidence from Trading the S&P." *Journal of Portfolio Management*, 23 (1997), 24-35.

Lettau, M., and S. C. Ludvigson. "Measuring and Modelling Variation in the Risk-Return Tradeoff." In Y. Ait-Sahalia, and L. P. Hansen (eds.), *Handbook of Finanical Econometrics*, 617–690. Amsterdam: Elsevier Science B.V. (2009).

Lo, A. W.; H. Mamaysky; and J. Wang. "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation." *Journal of Finance*, 55 (2000), 1705–1765.

Lo, A. W., and J. Hasanhodzic. *The Evolution of Technical Analysis: Financial Prediction from Babylonian Tablets to Bloomberg Terminals*. Hoboken, N.J.:John Wiley & Sons (2010).

Ludvigson, S. C., and S. Ng. "The Empirical Risk-Return Relation: A Factor Analysis Approach." *Journal of Financial Economcis*, 83 (2007), 171–222.

Ludvigson, S. C., and S. Ng. "Macro Factors in Bond Risk Premia." *Review of Financial Studies*, 22 (2009), 5027–5067.

Ludvisgon, S. C., and S. Ng. "A Factor Analysis of Bond Risk Premia." In A. Ulah, and D. Giles (eds.), *Handbook of Empirical Economics and Finance*, 313-372. London: Chapman and Hall (2011).

McCracken, M. W. "Asymptotics for Out of Sample Tests of Granger Causality." *Journal of Econometrics*, 140 (2007), 719–752.

Marquering, W., and M. Verbeek. "The Economic Value of Predicting Stock Index Returns and Volatility." *Journal of Financial and Quantitative Analysis*, 39 (2004), 407-429.

Menkhoff, L., and M.P. Taylor. "The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis." *Journal of Economic Literature*, 45 (2007), 936–972.

Moench, E. "Forecasting the Yield Curve in A Data-rich Environment: A No-arbitrage Factor-Augmented VAR Approach." *Journal of Econometrics*, 46 (2008), 26–43.

Neely, C. J.; P. Weller; and R. Dittmar. “Is Technical Analysis in the Foreign Exchange Market Profitable? A Genetic Programming Approach.” *Journal of Financial and Quantitative Analysis*, 32 (1997), 405–426.

Neely, C. J.; D. E. Rapach; J. Tu; and G. Zhou. “Forecasting the Equity Premium: The Role of Technical Indicators.” Working Paper, Federal Reserve Bank of St. Louis (2012).

Newey, W. K., and K. D. West. “A Simple, Positive Semidefinite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” *Econometrica*, 55 (1987), 703–708.

Park, C. H., and S. H. Irwin. “What Do We Know About the Profitability of Technical Analysis?” *Journal of Economic Surveys*, 21 (2007), 786–826.

Pástor, Ľ., and R. F. Stambaugh. “Comparing Asset Pricing Models: An Investment Perspective.” *Journal of Financial Economics*, 56 (2000), 335–381.

Pástor, Ľ., and P. Veronesi. “Uncertainty about Government Policy and Stock Prices.” *Journal of Finance*, 67 (2012a), 1219–1264.

Pástor, Ľ., and P. Veronesi. “Political Uncertainty and Risk Premia.” Working Paper, University of Chicago (2012b).

Pesaran, M. H., and A. Timmermann. “Selection of Estimation Window in the Presence of Breaks.” *Journal of Econometrics*, 137 (2007), 134–161.

Savin, G.; P. Weller; and J. Zvingelis. “The Predictive Power of “Head and Shoulders” Price patterns in the U.S. Stock Market.” *Journal of Financial Econometrics*, 5 (2007), 243–265.

Schwager, J. *Market Wizards: Interviews with Top Traders*. New York: Harper–Collins (1989).

Schwager, J. *The New Market Wizards: Conversations with America’s Top Traders*. New York: Wiley (1992).

Schwager, J. *Hedge Fund Market Wizards: How Winning Traders Win*. Hoboken: John Wiley & Sons (2012).

Schwarz, G. “Estimating the Dimension of A Model.” *Annals of Statistics*, 6 (1978), 461–464.

Sullivan, R.; A. Timmermann; and H. White. Data-Snooping, Technical Trading Rule Performance, and the Bootstrap. *Journal of Finance*, 54 (1999), 1647–1691.

Thornton, D. L., and G. Valente. “Out-of-Sample Predictions of Bond Excess Returns and Forward Rates: An Asset Allocation Perspective.” *Review of Financial Studies*, 25 (2012), 3141–3168.

Treynor, J. L., and R. Ferguson. “In Defense of Technical Analysis.” *Journal of Finance*, 40 (1985), 757–773.

Vayanos, D. “Flight to Quality, Flight to Liquidity, and the Pricing of Risk.” Working Paper, London School of Economics (2004).

Wachter, J. “A Consumption Based Model of the Term Structure of Interest Rates.” *Journal of Financial Economics*, 79 (2006), 365–399.

West, K. D. “Asymptotic Inference About Predictive Ability.” *Econometrica*, 64 (1996), 1067–1084.

Wright, J. “Term Premia and Inflation Uncertainty: Empirical Evidence from An International Panel Dataset.” *American Economic Review*, 101 (2011), 1514–1534.

Zhu, Y., and G. Zhou. "Technical Analysis: An Asset Allocation Perspective on the Use of Moving Average." *Journal of Financial Economics*, 92 (2009), 519–544.

TABLE 1
Summary Statistics for PC Factors $\hat{f}_t$

This table reports the summary statistics for the first three 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 MA^{fs} and 15 trading volume technical indicators MA^{OBV}, respectively, using full sample of time-series information from 1964:01 to 2011:12. 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 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 the sample covariance matrix of the technical indicators to the sum of all eigenvalues. Column $AR1_i$ reports the first-order autocorrelation coefficients for technical PC factor i.

	$\hat{f}^{fs}_{i,t}$		$\hat{f}^{OBV}_{i,t}$	
i	R^2_i	$AR1_i$	R^2_i	$AR1_i$
1	0.68	0.97	0.83	0.93
2	0.74	0.89	0.89	0.63
3	0.79	0.88	0.93	0.01

TABLE 2

In-sample Forecasting Results for Short-term Treasury Bonds, 1964:01−2007:12

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)				Yes		0.31
	(2)					Yes	0.23
	(3)	1.09	0.62				0.28
		(4.84)	(3.89)				
	(4)			1.20			0.10
				(2.46)			
	(5)	1.02	0.54	0.81			0.32
		(4.26)	(3.88)	(1.89)			
	(6)	0.27	0.21	0.69	Yes	Yes	0.49
		(1.67)	(2.07)	(1.78)			
$rx_{t+1}^{(3)}$	(1)				Yes		0.33
	(2)					Yes	0.19
	(3)	1.97	1.21				0.29
		(4.70)	(4.42)				
	(4)			2.12			0.10
				(2.33)			
	(5)	1.85	1.07	1.37			0.33
		(4.27)	(4.39)	(1.75)			
	(6)	0.55	0.46	1.22	Yes	Yes	0.49
		(1.81)	(2.47)	(1.69)			
$rx_{t+1}^{(4)}$	(1)				Yes		0.36
	(2)					Yes	0.16
	(3)	2.74	1.79				0.32
		(4.72)	(4.75)				
	(4)			2.78			0.09
				(2.30)			
	(5)	2.59	1.63	1.68			0.34
		(4.35)	(4.64)	(1.68)			
	(6)	0.82	0.73	1.52	Yes	Yes	0.50
		(1.85)	(2.82)	(1.64)			
$rx_{t+1}^{(5)}$	(1)				Yes		0.33
	(2)					Yes	0.14
	(3)	3.44	2.15				0.32
		(5.01)	(4.73)				
	(4)			3.21			0.08
				(2.19)			
	(5)	3.28	1.97	1.85			0.34
		(4.66)	(4.62)	(1.56)			
	(6)	1.37	0.99	1.72	Yes	Yes	0.47
		(2.43)	(2.99)	(1.52)			

TABLE 3
In-sample Forecasting Results for Short-term Treasury Bonds, 1964:01−2011:12

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 1964:01−2011:12. 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, is also included as a control variable. 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	R^2
$rx_{t+1}^{(2)}$	(1)				Yes	0.21
	(2)	1.06 (4.94)	0.58 (4.06)			0.26
	(3)			1.09 (2.46)		0.09
	(4)	0.98 (4.18)	0.53 (4.14)	0.70 (1.79)		0.30
	(5)	0.62 (2.88)	0.36 (3.21)	0.79 (2.01)	Yes	0.35
$rx_{t+1}^{(3)}$	(1)				Yes	0.22
	(2)	1.97 (4.88)	1.13 (4.46)			0.28
	(3)			1.89 (2.29)		0.08
	(4)	1.82 (4.29)	1.04 (4.49)	1.16 (1.73)		0.31
	(5)	1.12 (2.89)	0.72 (3.70)	1.33 (1.86)	Yes	0.36
$rx_{t+1}^{(4)}$	(1)				Yes	0.26
	(2)	2.75 (4.96)	1.67 (4.70)			0.29
	(3)			2.42 (2.18)		0.07
	(4)	2.58 (4.47)	1.56 (4.66)	1.35 (1.65)		0.32
	(5)	1.50 (2.73)	1.06 (4.03)	1.61 (1.75)	Yes	0.38
$rx_{t+1}^{(5)}$	(1)				Yes	0.24
	(2)	3.49 (5.30)	2.01 (4.62)			0.30
	(3)			2.77 (2.06)		0.06
	(4)	3.31 (4.85)	1.89 (4.59)	1.43 (1.60)		0.32
	(5)	2.16 (3.24)	1.36 (4.02)	1.71 (1.66)	Yes	0.36

TABLE 4
In-sample Forecasting Results for Long-term Treasury Bonds, 1981:07−2007:12

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 1981:07−2007:12. 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)				Yes		0.27
	(2)					Yes	0.05
	(3)	9.27	9.68				0.45
		(3.55)	(5.69)				
	(4)			10.08			0.08
				(2.09)			
	(5)	9.01	9.51	1.32			0.45
		(2.91)	(5.55)	(0.38)			
	(6)	6.88	8.19	2.03	Yes	Yes	0.47
		(2.04)	(4.76)	(0.85)			
$rx_{t+1}^{(18)}$	(1)				Yes		0.27
	(2)					Yes	0.05
	(3)	9.65	10.26				0.45
		(3.56)	(5.59)				
	(4)			10.17			0.07
				(2.01)			
	(5)	9.48	10.15	0.88			0.46
		(2.95)	(5.45)	(0.25)			
	(6)	7.30	8.77	1.57	Yes	Yes	0.47
		(2.09)	(4.74)	(0.62)			
$rx_{t+1}^{(19)}$	(1)				Yes		0.27
	(2)					Yes	0.05
	(3)	10.01	10.84				0.45
		(3.57)	(5.47)				
	(4)			10.20			0.07
				(1.93)			
	(5)	9.94	10.79	0.38			0.46
		(3.00)	(5.32)	(0.10)			
	(6)	7.70	9.34	1.05	Yes	Yes	0.48
		(2.15)	(4.71)	(0.40)			
$rx_{t+1}^{(20)}$	(1)				Yes		0.28
	(2)					Yes	0.05
	(3)	10.35	11.41				0.46
		(3.59)	(5.33)				
	(4)			10.15			0.06
				(1.87)			
	(5)	10.38	11.43	-0.19			0.47
		(3.05)	(5.18)	(-0.05)			
	(6)	8.08	9.91	0.48	Yes	Yes	0.48
		(2.20)	(4.66)	(0.17)			

TABLE 5

In-sample Forecasting Results for Long-term Treasury Bonds, 1981:07−2011:12

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 $n = 17, \ldots, 20$ over the period 1981:07−2011:12. 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, is also included as a control variable. 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	R^2
$rx_{t+1}^{(17)}$	(1)				Yes	0.19
	(2)	8.14 (3.58)	8.81 (4.77)			0.40
	(3)			7.45 (1.74)		0.05
	(4)	8.00 (2.94)	8.76 (4.76)	0.56 (0.18)		0.40
	(5)	6.21 (2.28)	7.79 (4.67)	1.47 (0.50)	Yes	0.42
$rx_{t+1}^{(18)}$	(1)				Yes	0.19
	(2)	8.40 (3.53)	9.33 (4.67)			0.40
	(3)			7.43 (1.65)		0.04
	(4)	8.35 (2.95)	9.32 (4.66)	0.18 (0.05)		0.40
	(5)	6.39 (2.25)	8.26 (4.61)	1.17 (0.39)	Yes	0.42
$rx_{t+1}^{(19)}$	(1)				Yes	0.19
	(2)	8.62 (3.49)	9.85 (4.56)			0.40
	(3)			7.34 (1.57)		0.04
	(4)	8.69 (2.97)	9.87 (4.54)	-0.27 (-0.08)		0.40
	(5)	6.54 (2.22)	8.72 (4.54)	0.81 (0.26)	Yes	0.42
$rx_{t+1}^{(20)}$	(1)				Yes	0.20
	(2)	8.82 (3.44)	10.35 (4.43)			0.40
	(3)			7.18 (1.48)		0.03
	(4)	9.01 (2.98)	10.42 (4.41)	-0.78 (-0.22)		0.40
	(5)	6.67 (2.19)	9.17 (4.45)	0.40 (0.13)	Yes	0.42

TABLE 6

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.

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 7
Out-of-sample Forecasting Results for Short-term Treasury Bonds, 1975:01−2011:12

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 1975:01−2011:12 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. 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. $\tilde{\mathbf{F}}^{TI}_t = (\tilde{\mathbf{F}}^{fs}_t,\ \tilde{\mathbf{F}}^{OBV}_t)$ includes both the forward spread and trading volume technical indicator factors. CP_t represents the Cochrane and Piazzesi (2005) forward rate factor. 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.

n	CP_t	$\tilde{\mathbf{F}}^{fs}_t$	$CP_t + \tilde{\mathbf{F}}^{fs}_t$	$\tilde{\mathbf{F}}^{OBV}_t$	$CP_t + \tilde{\mathbf{F}}^{OBV}_t$	$\tilde{\mathbf{F}}^{TI}_t$	$CP_t + \tilde{\mathbf{F}}^{TI}_t$
2	0.038*	0.185***	0.173***	0.070**	0.118**	0.209***	0.213***
3	0.029*	0.204***	0.178***	0.055**	0.093**	0.218***	0.206***
4	0.023*	0.215***	0.177***	0.045*	0.078**	0.223***	0.198***
5	0.031*	0.220***	0.198***	0.032*	0.072*	0.220***	0.206***

TABLE 8
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 $n = 17,...,20$ 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.

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 9
Out-of-sample Forecasting Results for Long-term Treasury Bonds, 1985:01−2011:12

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 1985:01−2011:12 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. 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. $\tilde{\mathbf{F}}^{TI}_t = (\tilde{\mathbf{F}}^{fs}_t,\ \tilde{\mathbf{F}}^{OBV}_t)$ includes both the forward spread and trading volume technical indicator factors. CP_t represents the Cochrane and Piazzesi (2005) forward rate factor. 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.

n	CP_t	$\tilde{\mathbf{F}}^{fs}_t$	$CP_t + \tilde{\mathbf{F}}^{fs}_t$	$\tilde{\mathbf{F}}^{OBV}_t$	$CP_t + \tilde{\mathbf{F}}^{OBV}_t$	$\tilde{\mathbf{F}}^{TI}_t$	$CP_t + \tilde{\mathbf{F}}^{TI}_t$
17	0.131***	0.343***	0.356***	−0.240	−0.034**	0.169***	0.159***
18	0.138***	0.357***	0.364***	−0.237	−0.026**	0.177***	0.167***
19	0.145***	0.368**	0.372***	−0.231	−0.016**	0.186***	0.177***
20	0.151***	0.375**	0.373**	−0.222	−0.004***	0.195***	0.186***

TABLE 10
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 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 $n = 2, ..., 5$ over 1975:01−2007:12 and 1975:01−2011:12 forecast evaluation periods, respectively, and Panels C and D report the average utility gains of long-term bonds with maturities $n = 17, ..., 20$ over 1985:01−2007:12 and 1985:01−2011:12 periods.

n	$\tilde{\mathbf{F}}_t^{TI}$	CP_t	$CP_t + \tilde{\mathbf{F}}_t^{TI}$	LN_t	$LN_t + \tilde{\mathbf{F}}_t^{TI}$	$CP_t + LN_t$	$CP_t + LN_t + \tilde{\mathbf{F}}_t^{TI}$
Panel A: Short-term Treasury bonds, 1975:01−2007:12							
2	0.71	0.17	0.67	-0.31	1.02	0.34	0.84
3	1.35	0.06	1.24	-0.73	1.78	0.32	1.36
4	2.06	0.35	1.95	-0.80	2.37	0.65	2.14
5	2.77	0.45	2.81	-0.60	3.01	0.69	3.06
Panel B: Short-term Treasury bonds, 1975:01−2011:12							
2	0.38	-0.37	0.33				
3	0.67	-1.07	0.55				
4	1.21	-1.23	1.00				
5	2.09	-1.23	1.95				
Panel C: Long-term Treasury bonds, 1985:01−2007:12							
17	3.73	2.83	3.16	-0.56	3.81	1.67	3.21
18	3.36	2.74	2.87	-0.40	3.56	1.76	2.94
19	2.84	2.60	2.44	-0.23	3.19	1.86	2.52
20	2.07	2.43	1.80	-0.03	2.63	2.00	1.90
Panel D: Long-term Treasury bonds, 1985:01−2011:12							
17	2.81	0.38	2.28				
18	2.57	0.45	2.01				
19	2.17	0.51	1.59				
20	1.56	0.54	0.95				