Forecasting Corporate Bond Returns:

A Regressed Combination Approach

Hai Lin

Victoria University of Wellington

Chunchi Wu

State University of New York at Buffalo

and

Guofu Zhou

Washington University in St. Louis*

First draft: April 6, 2013

Current version: Tuesday 10^{th} March, 2015

---

*Correspondence: Guofu Zhou, Olin School of Business, Washington University, St. Louis, MO 63130. Phone: (314) 935-6384 and e-mail: zhou@wustl.edu. We thank Michael Brennan, Douglas J. Fairhurst, Kenneth French, Yongmiao Hong, George Jiang, Jerry Kallberg, Glenda Kao, Sheen Liu, Mike McNamara, Brian McTier, Seth Pruitt, Ľuboš Pástor, Jack Strauss, Allan Timmermann, Jason Turkiela, Rossen Valkanov, seminar participants at National Taiwan University, Renmin University of China, Tsinghua University, Washington State University, Washington University in St. Louis, and Xiamen University and participants at the Q-Group Spring 2014 seminar, the 2014 Annual Missouri Economics Conference and the 2014 New Zealand Finance Colloquium for very helpful comments.

Forecasting Corporate Bond Returns:

A Regressed Combination Approach

Using a comprehensive data set, we find that corporate bond returns are not only predictable by traditional predictors (default spreads, term spreads, dividend yields, and issuer quality) but highly predictable based on a new regressed combination model that combines information from an array of 27 macroeconomic, stock and bond predictors. The predictive model based on the large set of variables outperforms existing models substantially, and delivers out-of-sample forecasts that are both statistically and economically significant and are closely linked to the real economy. Our results suggest that stock market and macroeconomic variables contain important information for future bond returns.

JEL classification: G12; G14;

Keywords: Predictability; corporate bonds; regressed combination; out-of-sample forecasts; utility gains.

There is a large body of literature on whether stock returns are predictable, and there is also an equally impressive number of studies on government bond returns, but only a handful of research on the predictability of corporate bond returns.[1] Keim and Stambaugh (1986) conduct perhaps the first major study on corporate bond return forecasting. Subsequently, Fama and French (1989) find that default spreads, term spreads and dividend yields can predict corporate bond returns both in- and out-of-sample. More recently, Greenwood and Hanson (2013) further identify issuer quality and Lin, Wang and Wu (2014) use liquidity and forward rate factors as additional predictors for corporate bond returns. The lack of studies on corporate bond return predictability is perhaps due to the fact that the data of individual bonds were not as readily available as those of stocks and government bonds. Recent availability of large publicly accessible corporate bond data offers an excellent opportunity to revisit this issue. Given that the market size of corporate bonds is almost as large as the stock market, it is important to understand their time-varying risk premia. Moreover, corporate bond return predictability is of interest not only for asset pricing and portfolio allocations, but also for understanding firms' interest rate exposure, which is a substantial source of financial risk to non-financial firms.

In this paper, we conduct a comprehensive study on the predictability of corporate bond returns by focusing on four major questions. The first question is what economic variables can have predictive power for corporate bond returns. The number of predictors used by Fama and French (1989), Greenwood and Hanson (2013), among others, are admittedly few. While these studies provide deep insights into why certain predictors should be looked at, they ignore other potentially important predictors and hence may underestimate the true predictability. A particular concern is that the economic value of a limited number of predictors prescribed by the existing studies is not very significant. From the investment and risk management perspective, maximizing return predictability is of great interest. In this paper, we consider three types of predictors which are

[1] See, for example, Fama and Schwert (1977), Fama and French (1988), Campbell and Shiller (1988), Campbell, Lo and MacKinlay (1997), Kothari and Shanken (1997), Pontiff and Schall (1998), Campbell and Vuolteenaho (2004), Lettau and Ludvigson (2001), Ang and Bekaert (2007), Rapach, Strauss and Zhou (2010), Henkel, Martin and Nardari (2011), Ferreira and Santa-Clara (2011) and Dangl and Halling (2012) for predicting stocks; and Fama and Bliss (1987), Campbell and Shiller (1991), Cochrane and Piazzesi (2005), Ludvigson and Ng (2009), Almeida, Graveline and Joslin (2011) and Goh, Jiang, Tu and Zhou (2011) for predicting government bonds.

relevant in theory for corporate bond returns: stock market, Treasury market and corporate bond market variables. We examine the predictive ability of these variables not only separately, but also jointly with a total of 27 predictors. Indeed, as we shall demonstrate, this comprehensive set of predictors improves the predictability of corporate bond returns dramatically.[2] Furthermore, the analysis of subgroup predictors reveals important economic sources of return predictability for bonds in different rating classes. For highly rated bonds, the Treasury market variables have the highest predictive power while for junk-rated bonds, the stock market predictors and the variables related to default premia are more powerful predictors. This finding suggests that expected returns of highly rated bonds are primarily driven by term structure factors and expected returns of low rated bonds are more closely linked to variables related to credit risk premia whose variations tied strongly to long-term prospects of business conditions.

The second question is how to combine the information from a large set of predictors to obtain optimal bond return forecasts. As shown by Welch and Goyal (2008) in the context of equity risk premium forecasts, a naive multiple regression of asset returns on a large number of predictors will over-parameterize the model and lead to poor out-of-sample forecasts. While the principal component analysis (PCA) is a popular method in the literature for extracting information from a large number of variables, the PCA in fact performs quite poorly out-of-sample too. A well-known econometric tool (see, e.g., Timmermann, 2006) is a combination method. First, predictive regressions are run on each predictor to obtain individual forecasts. Then a combination of the individual forecasts, such as their mean, serves as the forecast. In macroeconomic forecasting, Stock and Watson (2001) find that such a simple mean combination method is the favored strategy rather than using dozens of individual predictive models. Consistent with their finding, Rapach, Strauss and Zhou (2010) show that the mean combination method delivers a significant out-of-sample forecast of the equity risk premium.

As a methodological contribution, we provide a simple, generic idea to improve combination

[2]In the stock market, Rapach, Strauss and Zhou (2010), and Kelly and Pruitt (2013) are examples of using large sets of predictors to obtain significant predictability on the equity risk premium.

forecast methods. Motivated by Tu and Zhou's (2011) study on improving the $1/N$ portfolio rule, we consider an optimal portfolio of two forecasts, the sample mean and the combination forecast. This method yields a new forecast which is simply a predictive regression on the combination forecast. Since combination forecasts are widely used in econometrics and forecasting literature, our new methodology potentially has much broader implications beyond the scope of this paper. For simplicity, however, we shall focus on using two popular combination forecasts, the mean forecast and Bates and Granger's (1969) weighted-average forecast. We call the associate regressed combination forecasts as the regressed mean combination (RMC) and the regressed weighted-average combination (RWC) forecasts, respectively.

The RMC forecast has a close relationship to the partial least squares (PLS) forecast, which was first proposed by Wold (1966) and has recently been developed further by Kelly and Pruitt (2013, 2014). Kelly and Pruitt (2013) show that the PLS generates a powerful book-to-market ratio predictor of the stock market, and Huang, Jiang, Tu and Zhou (2015) find that the PLS provides a strong investor sentiment index for forecasting the equity risk premium. Interestingly, the PLS and the RMC in fact belong to the same class of forecasters in the special case of linear models, though the latter is more general and is applicable to nonlinear models as well. Hence, our proposed methodology not only advances the literature on combination forecasts, but also provides an alternative interpretation for the powerful PLS forecaster. Since our applications below show that the RWC can improve the RMC further, the RWC forecaster will be of our focus throughout this paper.

Empirically, we find that the RWC generates superior forecasts for corporate bond returns. For example, the RWC delivers an in-sample average R^2 of 11.22% at the monthly horizon across bonds of different ratings and maturities, which is almost three times as large as the in-sample average R^2 of 4% for the Fama-French model. In contrast, the popular PCA performs much worse, with an in-sample average R^2 of only 0.25%. Further, the predictive power of the RWC tends to increase with the return horizon locally. At the quarterly horizon, the in-sample R^2 of the RWC forecast increases to 15.64%, whereas it is capped at 8.52% for the Fama-French model. In out-of-sample forecasting, the RWC generates an average R^2 of 7.82% and 12.07% at monthly and quarterly horizons, respectively, compared with 3.58% and 7.28% for the Fama-French model. The results strongly suggest that the stock and bond market variables suggested in the recent literature have significant incremental predictive power over and beyond the traditional predictors of Fama and French (1989).

The third question is whether the predictability is of economic value. While Fama and French (1989) and Greenwood and Hanson (2013) find that the predictability of corporate bond returns is statistically significant, the issue of economic significance is not investigated. Considering an investor who has a mean-variance utility with risk aversion, we find that the average utility gains (annualized certainty equivalent returns) from ignoring the predictability completely to using the predictability based on the RWC are 5.74% (2.55%) at the monthly (quarterly) horizon. In contrast, the average gains are less than 1.58% for the best existing model, the Fama-French model, at both monthly and quarterly horizons, which are not economically significant at the conventional 2% cut-off point. Thus, our use of comprehensive bond and stock predictors and the new methodology produces distinctly better out-of-sample forecasts, which are not only statistically but economically significant.

The fourth question is what the economic sources are that drive the corporate bond return predictability. Fama and French (1989) are the first to link variations in expected corporate bond returns to business conditions. However, their inference is based only on in-sample forecasts. It is unclear whether or not the out-of-sample forecasts are also tied to business conditions. Similar to the case in the stock market (Henkel, Martin and Nardari, 2011), we find that corporate return predictability varies over business cycles. The out-of-sample predictability tends to be higher in a bad economy than in a good one. More importantly, we show that the RWC forecasts have strong predictive power for future economic activity based on a number of macroeconomic measures. This finding suggests that the primary source of the predictive power of this forecaster comes from its ability to forecast the real economy and to capture fundamental macroeconomic and term structure risks that drive the corporate bond risk premia.

Theoretically, Buraschi and Jiltsov (2007), and Joslin, Priebsch and Singleton (2014), among others, demonstrate that macroeconomic factors contain important information on bond term structure, and Campbell and Cochrane (1999), Bansal and Yaron (2004), and Zhou and Zhu (2015) show that macroeconomic factors drive the equity premium. To the extent that the corporate bond is a mixture of the government bond and equity, the corporate bond risk premium should also vary with macroeconomic conditions. Consistent with the existing theories, our results strongly suggest that the superior performance of the RWC is for the most part due to its ability in forecasting the changing macroeconomic conditions.

The remainder of the paper is organized as follows. Section I presents the methodology for assessing the return predictability of corporate bonds. Section II discusses data and Section III presents empirical results and robustness check. Section IV explores the economic sources of predictability. Finally, Section V summarizes the findings and concludes the paper.

I. The Methodology

In this section, we first present the theoretical motivation to our study, then a new econometric methodology that pools information from a large set of predictors, and finally a linkage with the PLS forecaster recently advanced by Kelly and Pruitt (2013).

A. Asset Pricing Motivation

Asset pricing models can in general be summarized into the stochastic discount factor form,

$$1 = E_t[r_{t+1} m_{t+1}], \tag{1}$$

where m_{t+1} is the stochastic discount factor that discounts the future payoff back to the current price, which is the return here once the current price is standardized as 1, and the expectation is conditional on the information at time t. It is important to note that all state variables that enter the pricing kernel m_{t+1} and all variables that are in the investor's information set can forecast the return, and it is just a matter of the degree of forecastability. Traditional term structure models allow some Treasury market variables and corporate bond market variables to enter m_{t+1}. Buraschi and Jiltsov (2007), and Joslin, Priebsch and Singleton (2014), among others, consider macroeconomic variables. Clearly, these variables are of relevance to corporate bond returns. Furthermore, intuitively stock variables should matter as well because corporate bonds and stocks are claims on the asset of the same firm and their returns should be driven by common fundamental factors (see Fama and French, 1993). Therefore, stock variables should in theory be useful for forecasting bond returns. While it is possible to conduct multiple regressions on each set of variables, in practicality running regressions on all variables is not econometrically sensible as it will be either infeasible or the model will perform poorly due to too many regressors. We address this issue in this paper.

B. Regressed Combinations

In forecasting future corporate bond excess returns, we use the standard predictive regression model:

$$r_{t+1} = \alpha + \beta_1 z_{1t} + \beta_2 z_{2t} + \cdots + \beta_N z_{Nt} + \varepsilon_{t+1}, \tag{2}$$

where r_{t+1} is the return of a corporate bond in excess of the riskless rate, z_{jt} is the j-th predictor at time t ($j = 1, \ldots, N$), and ε_{t+1} is an error term. For the Fama-French (1989, FF) model, $N = 2$ if the predictors are term spreads and default spreads (or $N = 3$ if dividend yields are also included).

When N is large, the predictive regression model is generally poorly behaved because of limited data in practice. For example, when $N = 14$, Welch and Goyal (2008) show that the "kitchen sink" regression with all predictors ends up with useless out-of-sample forecasts for the equity risk premium. In our case with $N = 27$, the problem is further compounded. A possible solution is to use forecast combination methods (e.g., Timmermann, 2006). The idea is first to run the predictive regression on each predictor to obtain individual forecasts,

$$\hat{r}_{t+1,j} = \hat{\alpha}_j + \hat{\beta}_j z_{jt} \tag{3}$$

where $\hat{\alpha}_j$ and $\hat{\beta}_j$ are the regression coefficients from the individual predictive regression. Then a combination of the N individual forecasts will be the forecast that utilizes the information of all predictors,

$$\hat{r}^c_{t+1} = w_1\hat{r}_{t+1,1} + w_2\hat{r}_{t+1,2} + \cdots + w_N\hat{r}_{t+1,N}, \tag{4}$$

where w_j's are the combination weights which sum to one. The simplest method is the mean combination with weights

$$w_1 = w_2 = \cdots = w_N = \frac{1}{N}.$$

Besides the mean combination or average forecast, the median and trimmed mean combinations are also often used. Bates and Granger (1969) propose another simple combination method that sets the weights to be inversely proportional to the estimated residual variances. This is known as the weighted-average forecast and will be a focus of this paper.

We can improve the combination forecasts from the perspective of portfolio diversification, an idea similar to that Tu and Zhou (2011) use to improve the well known $1/N$ portfolio rule. Consider for simplicity in-sample forecasts. Let $\bar{r}$ be the historical sample mean and $\hat{r}^c_{t+1}$ be the combination forecast. We are interested in a combination of them,

$$\hat{r}^*_{t+1} = (1-\delta)\bar{r} + \delta\hat{r}^c_{t+1} = \bar{r} + \delta(\hat{r}^c_{t+1} - \bar{r}), \tag{5}$$

where δ is a constant to be estimated to minimize the forecasting error. This forecast will be unbiased as long as $\hat{r}^c_{t+1}$ is unbiased. When $\delta = 0$, we use the sample mean forecast which is in fact the benchmark forecast under the assumption that the return is a random walk. In practice, this benchmark is not easy to beat. When $\delta = 1$, we rely on $\hat{r}^c_{t+1}$ completely. In general, unless one of them dominates the other, the above combination rule should theoretically do better than using either $\bar{r}$ or $\hat{r}^c_{t+1}$. This is similar to the portfolio choice of two assets, an optimal portfolio will always do better than investing in each asset individually unless the two assets are perfectly correlated.

Under the standard measure of mean-square forecasting error, δ can be estimated from the following regression,

$$r_{t+1} = \delta_0 + \delta(\hat{r}^c_{t+1} - \bar{r}) + u_{t+1}. \tag{6}$$

This essentially says that, based on any combination forecast, we can simply regress the return on it to get a regressed combination forecast.[3] When the combination forecast is the simple mean or the weighted Bates and Granger (1969) combination, we call the resulting r^*_{t+1} with δ estimated from (6) the regressed mean or weighted combination forecast (RMC or RWC).

Obviously, either RMC or RWC defined above can also be applied to generate out-of-sample forecasts. In this circumstance, the above regression, equation (6), is run recursively. At time t, only variables available at t are used to forecast the return at $t+1$. In this way, the forecast will not contain any future data and be out-of-sample.

To provide an intuitive explanation for why the regressed combination forecast can improve the forecasting performance, assume that the true return follows

$$r_{t+1} = 3\% + 0.02z_{1t} + 0.02z_{2t} + \varepsilon_{t+1}, \tag{7}$$

where z_{1t} and z_{2t} are the only two predictors that are independently distributed with mean zero and variance 1. Suppose further that there are no estimation errors, then the individual forecasts are given by

$$\begin{aligned}
\hat{r}_{t+1,1} &= 3\% + 0.02z_{1t}, \\
\hat{r}_{t+1,2} &= 3\% + 0.02z_{2t},
\end{aligned}$$

[3]For in-sample forecast, it makes no difference if we replace $(\hat{r}^c_{t+1} - \bar{r})$ by $\hat{r}^c_{t+1}$.

so that the mean combination forecast (as their simple average) is

$$\hat{r}^{c}_{t+1} = 3\% + 0.02 \times \frac{z_{1t} + z_{2t}}{2}.$$

This forecast has a variance of $0.02^2/2$. In contrast, the variance of the true forecast, the first three terms of equation (7), is 2×0.02^2. This clearly shows that the mean combination forecast underestimates the true variance. In general, when there are N independently distributed predictors that have the same betas, the variance of the true predictive component will be proportional to N, but the variance of the mean combination is proportional to only to $1/N$. The regressed combination forecast method corrects this problem, and hence it can improve the forecasting performance.

In the econometrics literature, Capistrán and Timmermann (2009) seems to be the first and only study that considers a regression on the combination forecast, but their study differs from ours in three major aspects. First, while their primary objective is to improve the average survey forecasts in the presence of the frequent entry and exit of individual forecasters, we focus on refining combination forecasts in predictive models. Second, they are interested in reducing bias, but we aim at correcting the variance of the combination forecast, and our ultimate goal is to provide better out-of-sample return forecasts in terms of the mean square error. Third, we shrink our forecast to the historical average, which is the conventional benchmark for assessing predictability.

However, it should be pointed out that in practice δ is estimated and the estimation errors are sample dependent. Therefore, while $\hat{r}^{*}_{t+1}$ is expected to outperform $\bar{r}$ and $\hat{r}^{c}_{t+1}$ in most applications, there is no guarantee that this will always be the case. This is because, when the sample size is small or the system is highly unstable, the errors in estimating δ can be large. Nevertheless, in our applications, this issue will not cause a serious problem. As will be shown, the regressed combination forecasts always outperform the initial combination forecasts substantially.

C. PLS and Beyond

Our paper differs from others by considering a large number of predictors that are related to future stock and bond returns. To maximize the benefits from a wealth of data, we employ an efficient method to extract the relevant information from this large set of predictors to obtain reliable forecasts. In a separate vein, the partial least squares (PLS) forecast method, pioneered by Wold (1966) and further developed by Kelly and Pruitt (2013, 2014), provides another powerful procedure for abstracting information from the large set of predictors. Therefore, it will be enlightening to compare our method with the PLS.

Interestingly, the regressed mean forecast, RMC, reduces to the PLS in the case of linear models, though the combination forecast applies to both linear and nonlinear models. To see this, recall the PLS assumes that the predictors have the following factor structure,

$$z_{it} = \lambda_{i0} + \lambda_{i,1} F_t + \lambda_{i,2} E_t + \varepsilon_{it}, \tag{8}$$

where F_t is the factor that contains relevant information for forecasting the corporate bond return, E_t is the common error component or non-informational factor that is irrelevant to the forecasting and ε_{it} is the idiosyncratic noise term associated with predictor i only.[4] For example, GDP and inflation may share a common noise component E_t that contains information important for foreign exchange rates but unimportant for forecasting corporate bond returns. The novel idea of the PLS is to estimate the latent factor F_t efficiently while at the same time eliminating the common error component E_t and idiosyncratic noise ε_{it}. As a result, the PLS performs better than the widely used principal component analysis (PCA), as shown empirically by Kelly and Pruitt (2013, 2014) and others. Econometrically, the PCA captures the covariance among the predictive variables and explains the largest faction of their total variations. However, by design it unfortunately contains the common error component that is irrelevant to the forecasting, which is why the PCA underperforms the PLS.

[4]The PLS here is the popular one-factor PLS. If there are multiple factors, the RMC only reduces to the first factor.

Mathematically, the PLS generates first an index of the predictors, $PLS_t = \sum_{i=1}^{N} \omega_i z_{it}$, and then forms the forecast from the following predictive regression

$$r_{t+1} = a + \beta_{PLS} PLS_t + v_t = a + \omega_1 \beta_{PLS} z_{1t} + \cdots + \omega_N \beta_{PLS} z_{Nt} + v_t. \tag{9}$$

Comparing this regression to (2), we have

$$\frac{\beta_i}{\beta_j} = \frac{\omega_i}{\omega_j} = \frac{\mathrm{cov}(r_{t+1}, z_{it})}{\mathrm{cov}(r_{t+1}, z_{jt})}, \tag{10}$$

where the last equality follows from the PLS algorithm in computing the index. On the other hand, it is straightforward to verify that the above equality also holds true for the RMC if the individual forecasts are obtained from univariate predictive regressions on the standardized predictors. Therefore, the two forecasters are analytically identical in the case of using univariate linear models in the mean combination.

Clearly, there are many combination methods, such as the weighted-average combination method, which will produce forecasts not the same as the PLS. For instance, the regressed weighted-average combination, the RWC, will generate a forecast that is different from the PLS forecast. Thus, the regressed combination method proposed in this paper is much more general than the PLS.

D. Out-of-sample Performance Measures

We conduct extensive out-of-sample analysis in addition to common in-sample studies (e.g., Greenwood and Hanson, 2013) in order to establish firmly the predictability of corporate bond returns. The out-of-sample forecast is exactly the same as the in-sample forecast except that it is done recursively. That is, if the out-of-sample forecast evaluation begins from time m, we use all available data or information up to time $t = m-1$, to estimate the parameters of the predictive model to construct the forecast of the excess return one period ahead, at time $t+1 = m$. This recursive forecast procedure applies to any future time until $T-1$. Following Campbell and Thompson (2008) and Pettenuzzo, Timmermann, and Valkanov (2014), we impose the economic restriction that the risk premium must be positive to be consistent with theory. Econometrically, the sign restriction can minimize the impact of volatile out-of-sample forecasts when a regression is estimated over a short sample period. However, we note that our results are robust to this restriction.

Following the convention in return forecasting (Fama and French, 1989; Campbell and Thompson, 2008), we evaluate the out-of-sample performance of the model relative to the updated historical average using the out-of-sample R^2 statistic:[5]

$$R^2_{OS} = 1 - \frac{\sum_{q=m}^{T-k}\left(r_{q+k} - \hat{r}_{q+k}\right)^2}{\sum_{q=m}^{T-k}\left(r_{q+k} - \bar{r}_{q+k}\right)^2}, \tag{11}$$

where r_{q+k} is the realized return at $q+k$, $\hat{r}_{q+k}$ ($\bar{r}_{q+k}$) is the out-of-sample forecast from the predictive regression model (historical average), q is the time that the forecast is made, k denotes the periods ahead in the forecast and T is the sample size. The out-of-sample R^2 gauges the improvement of the predictive regression model over the historical average forecast in terms of mean square prediction errors (MSPE). When $R^2_{OS} > 0$, the predictive regression forecast performs better than the historical average forecast. We test the statistical significance of R^2_{OS} by the p-value of the MSPE-adjusted statistic of Clark and West (2007), following the procedure in Rapach, Strauss and Zhou (2010).[6] For the forecast horizon longer than a month, we use the Hodrick (1992) method to account for the effect of overlapping residuals on standard errors.[7] Moreover, to assess whether adding variables significantly improves the predictive power of the model, we employ the test of Harvey, Leybourne, and Newbold (HLN, 1998). This test statistic is used to assess if a set of forecasting variables contains additional information not already in another set of forecasting variables. We use this method to test whether a predictive model encompasses another predictive model. If

[5]To our knowledge, Fama and French (1989) are the first to propose such a statistic, which are used by Welch and Goyal (2008) and Campbell and Thompson (2008) and known subsequently in many predictability studies as Campbell and Thompson out-of-sample R^2.

[6]To perform the test, we first compute the following square error difference: $\upsilon_{q+k} = \left(r_{q+k} - \bar{r}_{q+k}\right)^2 - \left[\left(r_{q+k} - \hat{r}_{q+k}\right)^2 - \left(\bar{r}_{q+k} - \hat{r}_{q+k}\right)^2\right]$, and then regress υ_{q+k} on a constant. The t-statistic of the constant term gives the p-value for the one-sided (upper tail) test.

[7]Correction by the Newey-West (1987) method gives similar results.

the forecast of a model is encompassed by another model, we say the latter has more predictive power than the former.

Following Campbell and Thompson (2008), we measure the economic significance of return forecasts. The measure is based on realized utility gains for a mean-variance investor who switches from ignoring predictability to using the predicted return calculated from the out-of-sample forecast.[8] The utility gain measure can also be interpreted as the fee investors being willing to pay to obtain the forecast instead of using the historical average. The procedure of measuring economic significance involves two steps. The first step is to determine the allocation of an investor's portfolio to risky bonds using the predictive model and the updated historical average. The proportion of the portfolio allocated to risky bonds depends on risk aversion and the return-to-variance ratio of the portfolio formed by the forecast of returns. The second step is to calculate the utility or certainty equivalent return from investing in the portfolio. Campbell and Thompson (2008) gives the detailed procedure of calculating the utility gains. A utility gain of 2% or more by the predictive model is usually considered to be economically significant.

II. The Data

Corporate bond data are collected from several sources: the Lehman Brothers Fixed Income (LBFI) database, Datastream, the National Association of Insurance Commissioners (NAIC) database, the Trade Reporting and Compliance Engine (TRACE) database and Mergent's Fixed Investment Securities Database (FISD). Using individual bond data to form portfolios, we examine return predictability for bonds with different ratings, maturities and other bond characteristics.

The LBFI database covers monthly data for corporate bond issues from January 1973 to March 1998. The data include month-end prices, accrued interest, rating, issue date, maturity and other bond characteristics. Datastream reports the daily corporate bond price averaged across all dealers

[8] This method is used by a number of studies (see, for example, Marquering and Verbeek, 2004; Welch and Goyal, 2008; Campbell and Thompson, 2008; Wachter and Warusawitharana, 2009).

for that bond. We choose US dollar-denominated bonds with regular coupons and obtain the data up to June 2012. The TRACE and NAIC databases contain transaction data for corporate bonds. TRACE coverage begins in July 2002 and NAIC data start from January 1994. TRACE initially covers only a subset of corporate bonds traded in the over-the-counter market and we supplement it by NAIC, which covers transactions primarily by insurance companies.[9] FISD provides issue- and issuer-specific data such as coupon rate, issue date, maturity date, issue amount, rating, provisions and other bond characteristics. We merge price data from all sources. Month-end prices are used to calculate monthly returns. The monthly corporate bond return as of time t is as follows:

$$R_t = \frac{(P_t + AI_t) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}}, \tag{12}$$

where P_t is the price, AI_t is accrued interest and C_t is the coupon payment, if any, in month t.[10] We discard the Datastream data if returns are available from other sources, and choose transaction-based data whenever these data are available. We exclude bonds with maturity less than two years and longer than 30 years and choose only straight bonds to evade confounding effects of embedded options. The sample period runs from January 1973 to June 2012.

From the literature of equity return forecasts (Welch and Goyal, 2008), we consider the following 14 variables as predictors.

1. Dividend-price ratio (log), D/P: Difference between the log of dividends paid on the S&P 500 index and the log of stock prices (S&P 500 index), where dividends are measured using a one-year moving sum.
2. Dividend yield (log), D/Y: Difference between the log of dividends and the log of lagged stock prices.
3. Earnings–price ratio (log), E/P: Difference between the log of earnings on the S&P 500 index

[9] The procedure of Bessembinder, Kahle, Maxwell, and Xu (2009) is used to filter out canceled, corrected and commission trades and daily prices are trade size-weighted average of intraday prices over the day.

[10] This return is transformed to the log return in the forecast, so that monthly log returns could be added together to get a return of longer horizon conveniently.

and the log of stock prices, where earnings are measured using a one-year moving sum.

4. Dividend–payout ratio (log), D/E: Difference between the log of dividends and the log of earnings.
5. Stock return variance, SVAR: Sum of squared daily returns on the S&P 500 index in a month.
6. Book-to-market ratio, B/M: Ratio of book value to market value for firms included in the Dow Jones Industrial Average.
7. Net equity expansion, NTIS: Ratio of the twelve-month moving sum of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.
8. Treasury bill rate, TBL: Interest rate on a three-month Treasury bill (secondary market).
9. Long-term yield, LTY: Long-term government bond yield.
10. Long-term return, LTR: Return on long-term government bonds.
11. Term spread, TMS: Difference between the long-term yield and the Treasury bill rate.
12. Default yield spread, DFY: Difference between BAA- and AAA-rated corporate bond yields.
13. Default return spread, DFR: Difference between long-term corporate bond and long-term government bond returns.
14. Inflation, INFL: Calculated from the CPI (all urban consumers).[11]

In addition, we use a number of variables considered to be important for predicting bond returns from the literature (see Collin-Dufresne, Goldstein and Martin, 2001; Baker, Greenwood and Wurgler, 2003; Cochrane and Piazzesi, 2005; Næs, Skjeltorp, and Ødegaard, 2011; Greenwood and Hanson, 2013). We discuss each of these variables below.

Stock market returns and the aggregate leverage ratio

Collin-Dufresne, Goldstein and Martin (2001) show that stock returns and leverage are important structural variables explaining yield spread changes. We use the S&P 500 index returns as a measure of the equity market return. For leverage, we use two aggregate leverage measures. First,

[11] Data were downloaded from Amit Goyal's website. These variables are used in Welch and Goyal (2008) and Rapach, Strauss and Zhou (2010). Also, since inflation rate data are released in the following month, following Welch and Goyal (2008), we use the one-month lag inflation data.

we average the leverage ratios of individual stocks listed in NYSE to give a measure of market aggregate leverage ratio (LEV1). The leverage ratio of an individual stock is measured by the book value of debt divided by the sum of the book value of debt and market value of equity, where the book value of debts is the sum of long-term debts and current liabilities obtained from COMPUSTAT. Second, we use the ratio of the aggregate book value of debt to the sum of aggregate book value of debt and market value of stocks listed in NYSE as another leverage measure (LEV2). The aggregate book value of debt and the aggregate market value of equity are the sum of book value of debt and the sum of equity value for all stocks listed in NYSE.[12] As the COMPUSTAT data used are quarterly, a linear interpolation is used to obtain monthly estimates (see also Collin-Dufresne, Goldstein and Martin, 2001). The market value of equity is the product of share price and the outstanding number of shares from the CRSP.

The Cochrane-Piazzesi term structure factor

Cochrane and Piazzesi (2005, hereafter CP) find that a single factor constructed from the full term structure of forward rates has high predictive power on excess returns of Treasury bonds. Lin, Wang and Wu (2014) find that the CP factor has predictive power for corporate bond returns. Following CP, we use the Fama-Bliss data of one- through five-year zero-coupon bond prices (available from CRSP) from 1973 to 2012 to estimate forward rates and their regression coefficients in the CP model, and construct the CP 5-year forward rate factor.[13] Besides the CP 5-year factor, we construct a CP 10-year factor using the forward rates up to 10th year similar to Lin, Wang and Wu (2014) to capture the information in distant forward rates.

The issuer quality factor

Greenwood and Hanson (2013) find that time-series variations in the average quality of debt issuers are useful for forecasting excess corporate bond returns. We include this variable as a predictor for bond returns. Similar to their study, we use the fraction of nonfinancial corporate

[12] When calculating the aggregate leverage ratio, we only use the stocks in NYSE that have financial statement data in COMPUSTAT.

[13] Estimates of forward rate coefficients in the CP regression model are $\hat{\rho}_0 = -1.52$, $\hat{\rho}_1 = -1.59$, $\hat{\rho}_2 = -0.09$, $\hat{\rho}_3 = 3.20$, $\hat{\rho}_4 = 0.81$ and $\hat{\rho}_5 = -2.08$. The adjusted R-squared is 25%.

bond issuances in the last 12 months with a junk rating as the issuer quality factor,

$$IQ_t = \frac{\sum_{j=0}^{j=11} Junk_{t-j}}{\sum_{j=0}^{j=11} Invest_{t-j} + \sum_{j=0}^{j=11} Junk_{t-j}}, \tag{13}$$

where $Junk_t$ is the par value of issuance with a speculative grade, and $Invest_t$ is the par value of issuance with an investment grade in month t. The monthly investment/junk bond issues for the period 1973–1993 are obtained from the Warga tape, and the monthly investment/junk bond issues for the period beginning from 1994 are obtained from FISD. High IQ_t tends to be followed by low corporate bond returns. For ease of interpretation, we add a negative sign to IQ_t to convert it into a bond quality measure, a higher value of which indicates better quality. This transformation makes the predictive relationship positive between quality of issuers and bond returns.

The debt maturity factor

Baker, Greenwood and Wurgler (2003) find that the share of long-term debt issues in total debt issues can predict government bond returns. It is possible that this predictor may also forecast corporate bond returns. We obtain the outstanding amounts of annual long- and short-term debts from the Federal Reserve Bank database and construct the monthly series of long- to short-term debt ratios using a linear interpolation. Baker, Greenwood and Wurgler (2003) find that when the share of long-term issues in the total debt issues is high, future bond returns are low.

The liquidity factor

The literature has documented a strong predictive relation between stock market liquidity and business cycle (see, for example, Næs, Skjeltorp, and Ødegaard (2011)). Since asset risk premia are related to business conditions, this finding implies that aggregate liquidity may predict corporate bond returns. We consider different liquidity measures including monthly changes in total money market mutual fund assets (ΔMMMF), on-/off-the-run spreads (Onoff), and the effective cost (EC) index of Hasbrouck (2009) for the stock market as predictors. Data for money market mutual fund assets are obtained from the Federal Reserve Bank. The on-/off-the-run spread is taken from the difference between the five-year constant-maturity Treasury rate from the Federal Reserve Bank and the five-year generic Treasury rate reported by Bloomberg system (see Pflueger and Viceira, 2011). The spread between on- and off-the-run bond yields captures the liquidity of the Treasury bond market (Duffie, 1996; Longstaff, Mithal and Neis, 2005). The spread may also reflect the financing advantage of on-the-run Treasury bonds in the special repo market (Jordan and Jordan, 1997; Buraschi and Menini, 2002; Krishnamurthy, 2002).

As liquidity has many dimensions, we use additional liquidity indices to capture more information. Two widely used marketwide liquidity indices in the literature are Pastor-Stambaugh (2003, PS) and Amihud (2002, Am) stock liquidity measures. The PS stock liquidity measure (PSS) is available from WRDS. We construct the Amihud stock (AmS) measures using the methods suggested by Acharya and Pedersen (2005). For ease of comparison with other illiquidity measures, we add a negative sign to the PS liquidity measure to make it consistent with the on-/off-the-run spread and Amihud measures, both are proxies for illiquidity. The converted PS index becomes a measure of market illiquidity.

Portfolios' yield spreads

Previous studies have found the bond yield contains important information for future bond returns (see, for example, Keim and Stambaugh, 1986; Greenwood and Hanson, 2013). However, the major information content of bond yields for expected corporate bond returns (or risk premiums) should be associated with yield spreads. To see why this is the case, consider the pricing formula of a corporate bond at time t:

$$P(y_t,t) = \sum_{i=1}^{i=n} Ce^{-y_t(T_i-t)} + FVe^{-y_t(T_n-t)}, \tag{14}$$

where C is the periodic coupon payment, y_t is the yield to maturity at time t, FV is the face value, and $T_i, i = 1,...,n$ is the time of the ith payment. Using the Taylor expansion, we can approximate the bond's excess return by

$$r_{t+1} = -D_t \Delta y_t + y_t - r_f^t, \tag{15}$$

where D_t is the duration of corporate bond at time t. Results show that the portfolio's yield spread (PYS), $y_t - r_f^t$, is a predictor for corporate bond excess returns.[14] Therefore, we include the yield spread as the predictor for bond returns. It is important to note that this predictor is distinguished from the default yield spread (DFY) of Fama and French (1989). The yield spread variable considered here is bond-specific. In empirical investigation, we test the predictability of bond portfolio returns. We hence calculate the yield spread for each rating and maturity portfolio for the predictive regression but this spread variable is still portfolio-specific.

Using the above mentioned predictors (27 in total), we consider the following predictive regressions:

1. The predictive regressions using the above individual predictors;
2. The predictive regressions using the combination and regressed combination predictors from the 27 individual predictors;
3. The predictive regression using the first principal component (PC) of all individual predictors;
4. The multiple predictive regression using term and default spreads as in Fama and French (1989), and then adding Treasury bill rates, lagged high-yield bond returns and the issuer quality factor as in Greenwood and Hansen (2013). In extended robustness analysis, we also run multiple regressions with all predictors and subsets of predictors and compare their performance with that of our regressed combination forecaster.[15]

Table 1 provides summary statistics for each predictive variable. We divide predictive variables into three groups: stock market, Treasury market and corporate bond market variables. The stock market variables include those predictors used in the equity return studies and liquidity indices constructed from stock transaction data. The Treasury bond market variables include those variables

[14] Lin, Wang and Wu (2014) also find that the duration-adjusted portfolio yield spread is useful for the prediction of corporate bond returns but they did not provide a rationale why yield spreads have information for expected bond returns.

[15] We have also examined other models used by Fama and French (1989) and found similar results which are available upon request.

which have been shown to have predictive power for Treasury bond returns and the liquidity measures for this market. Finally, the corporate bond market variables include default yield spreads, default return spreads, the issuance quality index and the debt maturity index. Previous studies have shown that these predictive variables are closely related to credit risk premia. Using different market variables in the regression allows us to see the role of each variable in the predictability of corporate bond returns as a whole and for bonds with different ratings and maturities.

[Insert Table 1 about here]

Table 2 summarizes the distribution of corporate bond data. Panel A shows that the data sample is well balanced across maturities and ratings. A-rated bonds assume the largest proportion, which have 302,794 observations and account for 40% of the sample. The speculative-grade bonds account for more than 10% of the sample, with 86,441 bond-month observations. Across maturities, long-term bonds (with maturity greater than 10 and less than 30 years) have the largest proportion. Among the data sources, LBFI contributes the most to the data sample (261,821 observations), followed by TRACE (261,063 observations), Datastream (147,486 observations) and NAIC (110,615 observations).

[Insert Table 2 about here]

We form bond portfolios by rating and maturity. To construct monthly returns of portfolios, we calculate mean returns of bonds in each portfolio. In each month, we sort all bonds independently into five rating portfolios and four maturity portfolios using the cut-off points of 5, 7 and 10 years, resulting in 20 portfolios at the intersection of rating and maturity. The short-maturity portfolio is constructed using the bonds with maturity less than five years, while the long-maturity portfolio is constructed using the bonds with maturity more than 10 years.

Panel B of Table 2 reports summary statistics for rating and maturity portfolios. The left panel reports the results of equal-weighted portfolios, while the right panel reports the results of value-weighted portfolios. Both mean and standard deviation of excess returns increase as the rating decreases. Long-maturity portfolios have higher mean returns and standard deviation.

To bring out the dynamics of bond returns, we transform the excess return series into the index (cumulative excess return) series by

$$I_t = I_{t-1}(1+r_t), \tag{16}$$

where r_t is the excess return of a corporate bond portfolio in month t. The initial value at time 1, which is January 1973 in our paper, is set to be 100. Thus, when there is a decrease in the index in month t, it means that the return of the portfolio is negative for that month.

Figure 1 plots the time series of the indices for all rating portfolios. The upper panel plots the indices of equal-weighted portfolios, while the lower panel plots the indices of value-weighted portfolios. There is an uptrend in these indices, suggesting that the investment in the corporate bond markets provides positive excess returns. However, in times of stress (such as the internet bubble in 2000, and the recent financial crisis in 2008–2009), the return drops substantially for junk bonds but remains quite smooth for AAA bonds. This pattern is attributable to flight-to-quality during the crisis period. In empirical tests, for brevity we only report results of value-weighted portfolios.

Our empirical tests are primarily based on the time series of corporate bond portfolio returns. Using the returns of portfolios constructed from the database of individual bonds allows us to control for the effects of bond provisions. We construct the portfolio return series by excluding bonds with embedded options (e.g., callable, putable and sinkable) to avoid the confounding effects associated with these options. Another advantage of using the return series constructed from the database of individual bonds is that we are able to obtain a longer time span for the return series. By contrast, existing indices of corporate bond returns do not have a unbroken long-span time series. Older corporate bond indices such as Salomon Brothers indices were suspended in 2001 while newer indices such as Barclays corporate bond indices are available only starting in 1988. The shorter time span of these index return series results in lower power in empirical tests. Also, these publicly available indices do not control for the effects of bond provisions and so are subject to the confounding effects of embedded options. Despite these drawbacks, we also report test results based on the Barclays index return series for comparative purposes and robustness check. The bottom panel of Figure 1 plots the return series of the Barclays indices which are obtained from the Bloomberg System. As shown, our portfolio returns exhibit a similar temporal pattern as Barclays corporate bond index returns.

[Insert Figure 1 about here]

III. Empirical Results

A. *In- and Out-of-sample Predictability*

To understand the role of individual variables in return prediction, we first run regressions of future returns of corporate bonds with different ratings against each predictor. The left panel of Table 3 reports in-sample R^2 values of the predictive regressions for each predictor listed in Table 1. The left side of the left panel reports results of monthly forecasts, and the right side shows quarterly forecasts. The results indicate that a number of variables associated with the stock and bond markets can predict corporate bond returns in-sample with a high R^2. Besides default spreads (DFY) and portfolios' yield spreads (PYS), variables with predictive power include term spreads (TMS), on-/off-the-run spreads (Onoff), and changes in money market mutual fund flows (ΔMMMF), long-term government bond returns (LTR), inflation rates (INFL), the Cochrane-Piazzesi forward rate factors (CP5 and CP10), leverage ratio (LEV2), earning-price ratio (E/P), dividend-payout ratio (D/E) and stock return variance (SVAR). These variables have R^2s higher than or comparable to that of default spreads.

Consistent with Joslin, Priebsch and Singleton (2014), we find that macroeconomic factors contain important information for expected corporate bond returns. More importantly, predictive variables vary in their ability to track bond returns of different rating classes. For AAA bonds, Treasury market variables such as long-term government bond returns (LTR), term spreads (TMS), Cochrane-Piazzesi forward rate factor (CP10), and on-/off-the-run spreads have good predictive power. In contrast, for speculative-grade bonds, stock market variables like E/P, D/E, and leverage ratio (LEV2), and default yield spreads (DFY) that are closely related to business and credit risks have high predictive power. In addition, on-/off-the-run spreads also have high predictive power, which appears to capture market liquidity conditions that affect all bonds. The main message we get from this table is that the best predictors for high-quality bonds are those that forecast the term structure whereas the best predictors for junk bonds are those that forecast credit risk premia.

[Insert Table 3 about here]

To see the individual relation between bond returns and predictors more closely, we report the covariance of each standardized predictor with bond returns in the right panel of Table 3. Since each predictor is standardized to have variance equal to one, the covariance is effectively the slope coefficient of the regressor in the univariate regression. Furthermore, the covariance of each predictor with bond returns reflects the weight or loading on each predictor when combining all variables into a single forecaster using either the PLS or our RMC method. As shown in the table, many of the predictive variables are significant (in boldface).

The results show that the traditional predictors, such as term spreads (TMS), default spreads (DFY), and Treasury bill rates (TBL), are indeed closely related to expected bond returns. More importantly, the stock market variables and other bond market variables also have high covariances with bond returns. These include earning yields (E/P), dividend payout (D/E), leverage ratios (LEV1 and LEV2), long-term government bond returns (LTR), inflation rates (INFL), CP factors (CP5 and CP10), percentage changes in the money market mutual fund flows (ΔMMMF) and on-/off-the-run spreads (Onoff). For the monthly horizon, on average the on-/off-the run spread has the largest covariance with returns. For the quarterly horizon, on average the portfolio yield spread PYS has the largest covariance with returns, followed by the CP10 forward rate factor. The fact that these variables are highly correlated with bond returns suggests that it is important to consider other variables than traditional predictors in forecasting corporate bond returns.

A particularly interesting finding that has an important economic implication and interpretation is that returns of low-grade bonds are more closely related with stock market variables. For example, the covariances of returns with earning yields (E/P), dividend payout (D/E), stock return volatility (SVAR), S&P 500 index returns (S&P 500), aggregate leverage ratios (LEV1 and LEV2), and effective trading cost (EC) are all highest for junk bonds, suggesting that stock market variables better track expected returns of these speculative bonds. This finding strongly supports the traditional view that speculative-grade bonds behave like stocks. Moreover, low-grade bond returns are closely linked to corporate bond market variables that are intimately related to credit risk premia. The covariances (slopes) of returns with default yield spread (DFY), issuance quality index (IQ), debt maturity index (DM) and portfolio yield spreads (PYS) are all highest (in absolute terms) for speculative-grade bonds. These findings provide clear evidence that the expected return of low-grade bonds contains a risk premium that is more strongly related to longer-term business and credit market conditions.

The results in Table 3 reflect rational pricing in the corporate bond market. The sign of the predictive variables is consistent with the risk premium theory. As shown, the slopes are positive for term spreads, default spreads, and the CP forward rate factor. These variables are well known measures of business cycles. The positive slopes of these variables capture the risk premia in bond returns which increase with business and interest rate risks. In addition, stock market predictive variables such as D/E, stock market volatility (SVAR), and leverage ratios (LEV) have positive slopes and E/P has a negative slope. This pattern is consistent with the rational asset pricing theory that when business-conditions risk is high or earnings are low, risk premia are high. Similarly, the slopes of credit risk variables such as DFY, IQ, PYS are positive while that of DM is negative. Consistent with the risk premium theory, the slope coefficients of all of these variables increase (in absolute terms) from high-grade to low-grade bonds. This trend is in line with the intuition about the credit risk of bonds, which is highly correlated with the business condition. Results show that the sensitivity of bond returns to unexpected changes in business and credit risks increases as the bond rating decreases. The slopes suggest that these predictive variables track components of expected corporate bond returns that vary with business and credit risk conditions.

The results in Table 3 show that individual predictors have varying predictive power and each of these predictors seems to contain information in different dimensions for returns of bonds with different quality and premium components (e.g., default and liquidity). This finding suggests that there is considerable room for combining individual forecasts to increase the predictive power of the model. The individual forecasts can be combined using the traditional methods such as mean, median, trimmed mean and weighted average combination methods. However, as we demonstrated earlier, the regressed combination method can substantially improve the performance of the predictive model. We next investigate this possibility based on the in- and out-of-sample results of forecasts for corporate bond returns.

The left panel of Table 4 reports the results of in-sample predictions by using typical combination methods and our new regressed combination methods. Besides the mean combination (MC) and the weighted-average combination (WC), we consider also the median combination (MD) and trimmed mean combination (TC). Consistent with the forecasting literature, the four combination forecasts are valuable in combining the information and produce in-sample R^2s which are larger than most of the individual forecasts reported in Table 3. Furthermore, the MC and WC appear to perform the best among the four combination methods.

Better than expected, the regressed combination methods further improve drastically the already impressive in-sample combination forecasts. As shown in the right panel of the table, each of the four regressed combination forecasts has substantially higher R^2 than its respective combination counterpart. For example, the in-sample R^2 of RWC for AAA bonds is 9.46, which is 4.6 times that of the WC. However, the RMD has much lower R^2 than that of the RWC, indicating that the relative performance of the regressed combination forecasts is linked to the strength of the underlying combination methods. Consistent with Kelly and Pruitt (2013), the RMC, which is equivalent here to the PLS, is a powerful predictor. Nevertheless, the RWC improves even further, and provides overall the best forecasts. All of the above results are robust to different ratings and maturities.

[Insert Table 4 about here]

We now compare the RWC forecast with three major alternative forecasts in the literature. The first is the PCA forecast that is based on the first principal component of all the predictors. The second is the Fama-French (1989, FF) model that uses default spreads and term spreads as predictors. The third is the Greenwood-Hanson (2013, GH) model that uses the Treasury bill rates, lagged high-yield bond returns and the issuer quality ratio as additional predictors.

The right panel of Table 4 compares the in-sample R^2s for different models. The results cover both the rating portfolios as well as the maturity portfolios in each rating category. The FF model performs well with an average in-sample R^2 of 4% for the monthly forecast, and 8.52% for the quarterly forecast. Though not reported in the table, the R^2s are 7.07% and 13.02% over 1973–1987, which covers part of the FF sample period, and 2.01% and 4.97% in the post-FF period 1988–2012, for monthly and quarterly forecast horizons, respectively. Although the predictability degenerates somewhat since the publication of their paper, the FF variables do have significant predictive power over time.

Surprisingly, GH performs worse than FF even in the in-sample forecast, though it has more predictors. This finding echoes previous studies on stock predictability that show adding more variables will not necessarily improve forecasting performance (see, for example, Welch and Goyal, 2008). The reason is that, econometrically, the predictive multiple regression tends to perform poorly with highly correlated regressors.

The principal component predictor PCA has the worst in-sample performance. All its R^2s are substantially below 1%. This level of predictability is not economically significant even in sample. In contrast, both the FF and GH models provide much better predictions of bond returns than the PCA. But the RWC outperforms all of them substantially while the FF model emerges as the distant second best predictive model.

The last column (Δ) for each forecast horizon in the right panel reports the difference in the R^2 values between the prediction using the RWC predictor and that using the FF model, to further highlight the improvement of the RWC. The differences are all positive, with the maximum value equal to 10.48% for the monthly forecast and 10.53% for the quarterly forecast. The superior performance of the RWC is robust across ratings and maturities. The results suggest that relying on the FF model will substantially underestimate the true predictability, and that there is value of using a large set of predictors.

It is known that good in-sample results do not warrant good out-of-sample forecasts. We next investigate the out-of-sample forecasting ability of different models, which are considered to be generally a more stringent test of return predictability. The left panel of Table 5 reports out-of-sample R^2s of the four forecasting combination methods and their regressed analogues. There are several major findings. First, all of the combination methods deliver positive and statically significant R^2s, implying that they are indeed robust forecasting procedures that are able to predict returns both in and out of sample. Second, the MD seems to have the worst performance among the four combinations, suggesting that the forecasts across individual predictors are asymmetric. Third, the regressed combinations improve their original combinations substantially. Although the improvement is somewhat lower than the in-sample case, the R^2s are often doubled. Overall, the results strongly suggest that the regressed combination is a powerful method for obtaining more efficient forecasts.

[Insert Table 5 about here]

To see how the regressed combinations improve their originals, Figure 2 plots the time series of realized returns and the returns predicted by the WC and RWC for AAA bonds with long maturity as an example (results for other ratings and maturities are similar). The result shows that the WC produces forecasts which are too smooth compared with actual returns. In contrast, the RWC method is able to track bond returns much better. In other words, the WC forecast considerably underestimates the true variance of the bond return and misses out important short-term variations, while the RWC corrects this problem. This is also true, though unreported here, for the MC and RMC. The results are consistent with our earlier analysis that the combination forecast tends to have lower variance than the true one.

[Insert Figure 2 about here]

We next compare the out-of-sample performance of the RWC with the other three predictive models, PCA, FF and GH. Note that when performing the out-of-sample forecast at time t, we only use the available information up to time t to perform forecasts. Hence, the principal component analysis (PCA) method uses available information from all predictors only up to t, and the FF and GH are based on recursively regressions.

The right panel of Table 5 compares the out-of-sample R^2 of the four predictive regression models. Similar to the in-sample results in Table 4, FF and GH have sizable out-of-sample predictive ability. The out-of-sample R^2 for all bonds using the FF model is 3.58% for the monthly forecast, and 7.28% for the quarterly forecast. The results for the GH model are much weaker but still significant. The worst performer is the PCA. Most of the out-of-sample R^2s of PCA are negative, suggesting that the principal component analysis is a poor method for out-of-sample forecasting.

The RWC has the best out-of-sample predictive performance among the four models (see the last column of the left panel and the first column of quarterly results in the right panel). All out-of-sample R^2s are significantly positive. For the monthly forecast, it can be as high as 11.98% (AA short-maturity portfolio). The average out-of-sample R^2 of the RWC is 7.82% for all bonds at the monthly horizon. For the quarterly forecast, the highest R^2 is 17.68% (AA short-maturity portfolio) and the R^2 for all bonds is 12.07% for all bonds. Both are much higher than the out-of-sample R^2s of FF and GH. Interestingly, these out-of-sample R^2s are substantially higher than those for forecasting the stock risk premium. For example, Rapach, Strauss and Zhou (2010) report an out-of-sample R^2 of only about 1% for the quarterly forecast during 1975–2005. Hence, the results suggest that the corporate bond market is much more predictable than the stock market.

The last column (Δ) for each forecast horizon in the right panel reports the differences in out-of-sample R^2 values between the RWC and FF. All of the differences are overwhelmingly positive, indicating that the RWC model has a higher predictive power than the FF. The improvement of monthly forecasts by the RWC is greater than that of quarterly forecasts. Similar to in-sample results, the improvement is quite robust across ratings and maturities, and is attributable to the better use of the information in a large set of predictors.

B. Economic Significance

Table 6 reports results of economic significance measured by utility gains or certainty equivalent returns (CER). The risk aversion coefficient is set equal to five and the optimal weight is between zero (short-sales constraint) and five.[16] The left panel reports the results of monthly forecasts, while the right panel reports quarterly forecasts. As in the case for the out-of-sample R^2s, we compare the four models: RWC, PCA, FF and GH.[17]

[Insert Table 6 about here]

Consistent with the out-of-sample R^2 values, the utility gains of the RWC are much larger than those of the FF, which in turn are often much larger than those of the GH and PCA. The utility gains of the RWC are all positive except for only one case for junk bonds with long maturity. Even in this particular case, the RWC still performs the best among the four models at the monthly forecast horizon. Across rating and maturity portfolios, the utility gains of the FF model are mostly economically insignificant. Similar to the results based on R^2s, the GH model performs substantially worse than the FF model, while the PCA is the worst performer whose gains are all negative except for BBB bonds with long maturity.

The last column in both panels of Table 6 reports the differences in utility gains between the RWC and FF models. These differences are overwhelmingly positive for both monthly and quarterly forecast horizons. The improvement in economic value by the RWC is greater for the monthly

[16] Rapach, Strauss and Zhou (2010) assume a risk aversion coefficient of three and the optimal weight between zero and three. Thornton and Valente (2012) assume a risk aversion coefficient of five and the optimal weight between minus one and two. Goh, Jiang, Tu and Zhou (2011) assume a risk aversion coefficient of five and the optimal weight less than eight.

[17] We have tried other risk aversion coefficients and other methods such as GISW (Goetzmann, Ingersoll, Spiegel and Welch, 2007) and Sharpe ratio, and find that our results are robust to these different specifications

forecast, and results are again robust across ratings and maturities.

Overall, results show that the gains of the out-of-sample forecasts by the RWC are not only statistically significant as shown before, but also economically significant. For the monthly forecast, the utility gain is 5.74% for the sample that includes all bonds. For the quarterly forecast, the gain is 3.77% for all bonds. The utility gains of the RWC are much larger than other models and also considerably higher than those in the stock market reported by Rapach, Strauss and Zhou (2010), suggesting there is substantial economic value of using a large set of predictors and the proposed methodology.

C. Forecast Encompassing Tests

To further evaluate the performance of different models, we conduct forecast encompassing tests. If the RWC forecaster has successfully extracted all relevant information in individual predictors, then adding the variables in the Fama-French and Greenwood-Hanson models should not improve the forecasting power of the RWC model. The encompassing test discriminates the performance of competing models based on this criterion.

We calculate the HLN statistics of Harvey, Leybourne, and Newbold (1998) to test whether the forecast by the RWC model encompasses the forecasts by the FF, GH and PCA models or vice versa. Table 7 reports the results of encompassing tests based on monthly return forecasts for different ratings and maturities. The null hypothesis is model 1 forecasts encompass model 2 forecasts against the one-side alternative hypothesis that the former does not encompass the latter. As shown in the table, the RWC model encompasses the FF, GH, and PCA models. Results suggest that the RWC is more efficient than the other three models in utilizing the information of individual predictors. By contrast, the FF, GH and PCA models all fail to encompass the RWC model. Results strongly suggest that the RWC model contains the information in the FF, GH and PCA models. Unreported results show a similar finding at the quarterly forecast horizon. These findings confirm the superiority of the RWC model and suggest that it provides the optimal forecast for corporate bond returns relative to other models.

[Insert Table 7 about here]

D. *Predictions Using Treasury Market Variables vs. Other Market Variables*

An important issue is about the roles of Treasury market variables versus other market variables in predicting corporate bond returns. Safe bonds (e.g., AAA) behave more like government bonds and risky bonds (e.g., junks) behave more like stocks. Intuitively, the former is likely to be affected more by Treasury market variables (e.g., discount rates) and the latter by the variables of the stock and other markets such as high-yield bonds. Thus, Treasury market variables are likely to track the premia for safe bonds more closely, and stock market variables and credit risk variables in the corporate bond market track the premia for risky bonds better. Table 3 has provided some evidence supporting this hypothesis. In this section, we test this hypothesis more formally. We construct the RWC predictor using only Treasury market variables and calculate its out-of-sample R^2 of corporate bond return forecasts. The difference between the out-of-sample R^2 of the RWC predictor extracted from Treasury market variables and that of the RWC predictor based on all variables, including the stock, corporate bond and Treasury market variables, measures the contribution of predictive variables other than the Treasury market variables.

We use alternative criteria to determine whether bonds have the characteristics of government bonds or stocks. Besides the rating, we consider default risk measured by expected default frequency (EDF) estimated from the Merton (1974) model, and stock market return betas. We employ the iterative procedure proposed by Bharath and Shumway (2008) and Gilchrist and Zakrajšek (2012) to estimate the EDF from the Merton model. To estimate market return betas, we run regressions of individual bond excess returns using a two-factor model with the term spread and stock market returns. The term spread factor is measured by the return difference between long-term government bond and one-month Treasury bill rates and the stock market factor is measured by the excess return of S&P 500 index. The term spread captures the effect of interest rates whereas the S&P 500 index return captures the effect of the market factor. We use the beta of stock market returns to sort the bonds into five beta portfolios. The portfolio return is the value-weighted average of individual bond returns in a portfolio. Bonds in the portfolio with a high beta have high sensitivity to stock market returns and so stock market variables should contribute more to the forecast of these bond returns. Similarly, we use expected default frequency to sort bonds into five EDF portfolios. As bonds in the portfolio with high EDF have high default risk, stock market variables are likely to contain more information for these bonds. Conversely, bonds in the portfolio with low EDF have low default risk and so Treasury market variables are likely to contain more information for these safe bonds.

Table 8 reports results of out-of-sample forecasts using the RWC predictor for each portfolio formed by the rating, beta and EDF. The percentage measure is the ratio between the out-of-sample R^2 of the RWC predictor using Treasury market variables only and the out-of-sample R^2 of the RWC predictor using all variables. Results strongly suggest that Treasury market variables play a much more important role for the bonds that have a high rating (e.g., AAA), low default risk and low beta. The ratios of the out-of-sample R-squares of the RWC predictor using Treasury market variables to that of the RWC predictor using all variables have the highest value for these bonds. Conversely, the ratios are the lowest for junk bonds and bonds with high EDF and betas. Results support the hypothesis that Treasury market variables are better predictors for safe bonds, and stock and other market variables are better predictors for risky bonds. Thus, Treasury and other market variables track different components of expected returns for different types of bonds. For high-quality bonds, the Treasury market variables track the term or maturity premium which is the main component of expected returns of these safe bonds. For low-quality bonds, the stock and corporate bond market track the credit risk premium which is the dominant component of expected returns for these risky bonds.

[Insert Table 8 here]

E. Longer Horizon Forecasts

We have shown thus far that corporate bond returns are highly predictable at monthly and quarterly horizons. Predictability of corporate bond returns however goes beyond these horizons. Table 9 reports return forecasts at longer horizons ranging from two quarters to one year. For brevity, we report only the results for speculative-grade bonds as results for other ratings show similar patterns. Results continue to show that returns are predictable at longer horizons. For the in-sample forecasts, the RWC model continues to perform much better than the Fama-French model. The improvement in in-sample R^2 by the RWC over the FF model is quite substantial and increases with the forecast horizon. The increase in R^2 range from 15.3 percent to 20.5 percent for the whole sample that includes all bonds. Similarly, the out-of-sample forecasts show predictability at longer horizons. The RWC model consistently outperforms the FF model across all horizons. The out-of-sample R^2 of the RWC are quite high, ranging from 23.5 percent to 28.1 percent from two quarters to one year horizon.

The predictability of returns at longer horizons is also of economic significance. As shown at the bottom panel of Table 9, the utility gains from using the RWC model are overwhelmingly positive. For the whole sample including all bonds, the RWC model delivers higher economic value than the FF model by a margin of 2.87 to 3.20 percent in terms of CER. Results show that the economic value of using the RWC predictor is significant and much higher. Overall, there is evidence that returns are predictable and return prediction is of economic value over various forecast horizons out-of-sample.

[Insert Table 9 about here]

F. Multiple Regressions

Recall that all together we have 27 predictors consisted of three types: stock, Treasury and corporate bond market variables. In this subsection, we examine how well each set of variables fares with others in a multiple regression and with the RWC forecaster in terms of out-of-sample forecasting performance.

We consider four multiple regression models using different sets of predictors in a horse race: (1) stock market variables; (2) Treasury market variables; (3) corporate bond market variables; and (4) all variables. The first two models enable us to see the natural economic relationship between corporate bond returns and variables in the stock and Treasury markets. If the Treasury (stock) market variables forecast AAA (junk) bonds better, the traditional multivariate regression should naturally reveal this relationship. The remaining models give additional information about the role of corporate bond market variables and important variables in the three markets.

We perform out-of-sample forecasts of these multiple regression models and compare their performance with the RWC model in terms of R^2. Table 10 reports the improvement of the RWC model over each multiple regression model. The improvement by the RWC is quite substantial across most models. For example, in column 1, the RWC model outperforms the multiple regression model using stock market variables by 19.85 percent for the sample including all bonds. The regressed weighted combination of all variables produces much higher predictive power than just direct inclusion of stock variables across all ratings. Column 2 shows the improvement of the RWC over the multiple regression model that includes only the Treasury bond market variables. Results show that the improvement is much higher for speculative-grade bonds than for AAA bonds. Using only the Treasury market variables as predictors thus underestimates the predictability of returns more for low-grade bonds than for high-grade bonds. This result suggests that the Treasury market variables forecast the return of AAA bonds much better than that of junk bonds, consistent with the results in Table 8. Column 3 shows that the improvement of the RWC over the model with the corporate bond market variables is fairly even across ratings suggesting that corporate bond market variables are important predictors across bonds of different ratings.

A more surprising finding is in column 4 which uses all variables in the multiple regression. Consistent with the finding of Welch and Goyal (2008), this ”kitchen sink” model performs much worse than other multiple regression models using only a subset of variables. As demonstrated by Rapach et al. (2010), the ”kitchen sink” model performs worse because each variable contains noise or false signals and the compounded errors from a large number of predictors can seriously compromise the model’s forecasting ability for stock returns. Hence, it is suboptimal to include all variables in the multiple regression model. Our results for corporate bond returns confirm this prediction. As shown, the out-of-sample R-squares are considerably lower for the ”kitchen sink” model by a huge margin of 32 to 43 percent across ratings compared to the RWC forecasts.

[Insert Table 10 about here]

G. Predictability on Hedged Returns and Index Returns

A potential concern is that corporate bond returns are predictable because the variables used in our model largely forecast the term structure and the riskfree (Treasury) bond return is an important component of the corporate bond return. In this subsection, we address this issue by directly forecasting the hedged return in which we control for the return on US Treasuries over the same maturity window. In essence, the hedged return is simply the return compensating investors for taking credit risk. Moreover, we conduct forecasts using indexes of corporate bond returns to compare with the results we have so far based on portfolios of individual bond returns for robustness.

To calculate the hedged return, we first obtain the price of the equivalent bond that has the same coupon and maturity as the corporate bond by discounting the coupons with the Treasury spot rates matching the time of each coupon and the principal payment. The spot rates are taken from Gurkaynak, Sack and Wright (2007). We then subtract the return of this riskless equivalent bond from the return of corporate bond to generate the hedged return (the corporate bond return in excess of the riskfree bond return). Specifically, the hedged return is simply the return of the portfolio with a long position in the corporate bond and a short position in a riskfree bond that has the same coupon and maturity as the corporate bond. For the return based on the index, we calculate the excess bond return by taking the difference between the Barclays corporate bond index return and the one-month Treasury bill rate.

Table 11 reports the results of in- and out-of-sample forecasts based on the hedged and excess returns of corporate bonds. The upper panel reports the results for portfolios of individual bonds and the lower panel reports results for index excess returns. Results continue to show that the RWC has high predictive power for hedged returns. Thus, the predictive power of the model for the corporate bond return is not derived from its predictive power for the Treasury return alone. The RWC model again outperforms the FF model considerably both in- and out-of-sample.

The lower panel of Table 11 reports the in- and out-of-sample results of index excess return forecasts. Results show that the RWC model performs quite well compared to the FF model. The improvement by the RWC forecasts increases as the rating decreases. On average, the in- and out-of-sample R-squares of the RWC are substantially higher those for the FF model. Thus, the regressed combination forecast model appears to perform very well for both portfolio returns generated from individual bond series and existing index returns complied by Barclays.

[Insert Table 11 about here]

IV. What Drives the Predictive Power?

The analysis above shows that bond and stock market variables contain important information for expected corporate bond returns and the RWC is an effective method for extracting such useful information from these variables. In this section, we investigate the performance of the RWC under different economic regimes to see if the predictability is related to the change in macroeconomic risks. Following this, we examine how the RWC predictor links to economic fundamentals to understand more about the source of its predictive power.

A. Economic Regimes

Fama and French (1989) suggest that during economic downturns, income is low and so expected returns on corporate bonds should be high in order to provide an incentive to invest. In general, heightened risk aversion when economic conditions are poor demands a higher risk premium, thereby generating risk premium predictability. Consistent with this hypothesis, Rapach, Strauss and Zhou (2010) find that the predictability of stock returns varies with business conditions and risk premium forecasts are closely related to business cycles. Particularly, out-of-sample gains for the market risk premium forecast are tied to business conditions and tend to be greater when business conditions are poorer.

In light of the literature, we examine the predictability of corporate bond returns over periods with different rates of economic growth. To accomplish this, following Rapach, Strauss and Zhou (2010), we sort the sample period based on the real GDP growth rates and divide them into good, normal and bad growth periods using the top, middle and bottom third sorted real growth rates, and then examine the performance of the RWC in terms of out-of-sample R^2s.

Table 12 reports the results of the out-of-sample performance during "good", "normal" and "bad" growth periods between 1983 and 2012. Results show that return predictability is much stronger during the low-growth period than during the high-growth period.[18] This pattern is consistent with the findings of Rapach, Strauss and Zhou (2010) and Henkel, Martin and Nardari (2011) that stock returns are much more predictable during "bad" growth periods. Hence, it appears that across stocks and bonds, the return predictability is driven by the same fundamental forces such as financial constraints and changing business conditions and risk aversion. Table 12 further shows that the discrepancy in the predictability between bad and good economies widens for long-maturity lower-quality bonds which have higher exposure to business cycle.

[Insert Table 12 about here]

B. Links to the Real Economy

Cochrane (2007) suggests that return forecasts are more plausibly related to macroeconomic risk if the return predictors also demonstrate an ability to forecast business cycle. The predictability

[18]Unreported results show that similar results hold for Treasury bond returns in different economic regimes.

can then be more credibly attributed to time-varying risk premiums due to changing risks or risk aversion. In what follows, we examine whether the RWC predictor can forecast real economic activity.

Consider the following predictive regression,

$$\Delta Y_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}, \tag{17}$$

where ΔY_{t+1} is the change in macroeconomic conditions in the next period, and X_t is the RWC predictor for a given bond portfolio in the current period. In this regression, we examine how the RWC predictor is related to the future state of the economy. Since the PCA is widely used for predicting returns, it is of interest to compare the RWC with the PCA in this context. To do so, we simply run similar regressions with X_t replaced by the PCA predictor.

We employ the following measures of Y_{t+1} in the predictive regression:

1. Smooth recession probability (SRP). The data of smooth recession probability are obtained from the Federal Reserve Bank of St. Louis. This recession probability is estimated by the dynamic-factor Markov-switching model of Chauvet (1998) using four monthly coincident variables: non-farm payroll employment, the index of industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales.
2. Industrial production growth (IPG). The production growth rate data are also obtained from the Federal Reserve Bank of St. Louis.
3. Treasury bill rates (TBL).
4. Default yield spreads (DFY).
5. Implied volatility index (VIX). VIX is the implied volatility of S&P 500 index options, which reflects the expectation of stock market volatility over the next 30-day period. It is widely used as a gauge of fear (Remolona, Scatigna and Wu, 2008; Whaley, 2009). Longstaff, Pan, Pedersen and Singleton (2011) use it to calculate the global risk premium. The data are downloaded from Chicago Board Options Exchange (CBOE).

6. Expected default frequency (EDF). The EDF is the mean of individual firms' expected default frequencies calculated from the Merton (1974) model.
7. Chicago Fed National Activity Index (CFNAI). The CFNAI is a monthly index designed to capture economic activity and inflationary pressure. It is similar to the index of economic activity developed by Stock and Watson (1999). The CFNAI data are downloaded from the Federal Reserve Bank of Chicago.
8. Aruoba, Diebold, and Scotti (2009) business conditions index (ADSI). This index tracks real business conditions at high frequency. The economic indicators underlying this index are initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and real GDP. The ADSI data are downloaded from the Federal Reserve Bank of Philadelphia.

Table 13 reports results of the predictive regression in (17) at quarterly horizons.[19] The t-values are calculated using the Newey-West (1987) adjusted standard errors. The results strongly indicate that the RWC predictor has high predictive power for the future change in economic conditions. Among all macroeconomic measures, only the results for Treasury bill rates (TBL) are not significant. The predictive power of the RWC varies across bond ratings. The RWC predictor associated with lower-grade bonds has much higher predictive power than that associated with higher-grade bonds. For example, when forecasting the SRP (recession probability), the adjusted R^2 of the RWC predictor of the BBB bond portfolio is 9.52%, while it is only 3.62% for the RWC predictor of the AAA bond portfolio. The results for other macroeconomic variables show a similar pattern. These findings suggest that the RWC predictor of lower-grade bonds contains substantially more information for future economic growth than that of higher-grade bonds. Intuitively, economic growth affects future cash flow, which is more important for the pricing of low-grade bonds than for the pricing of high-grade bonds.

In contrast, none of the results using the PCA to predict future economic conditions is significant and the adjusted R-squares are extremely low, suggesting that the PCA is not a good predictor

[19]We obtain similar results at monthly and yearly horizons.

for the future economic condition. This finding sheds light on the reason why the PCA is a poor predictor for bond risk premiums as shown earlier.

In summary, our empirical results strongly suggest that the predictive power of the RWC forecaster is derived from its ability to forecast future macroeconomic conditions. Economic fundamentals are the forces driving time variations in expected corporate bond returns and the RWC does a good job in tracking the temporal movement of these forces. This explains why the RWC predictor performs much better than the popular PCA factor in predicting bond returns. This evidence further confirms that the RWC extracts the information from individual predictive variables much more efficiently than the PCA.

[Insert Table 13 about here]

V. Conclusions

In this paper, we provide a comprehensive study on the predictability of corporate bond returns. We consider a large number of individual predictors, including stock, Treasury and corporate bond market variables to predict corporate bond returns, and propose a new method, the regressed combination, to combine the information from a large set of predictors. We find that the model of the regressed weighted-average combination (RWC) forecast performs substantially better than the Fama-French (1989) model, the Greenwood-Hanson (2013) model, the traditional combination forecasts, multiple regression models, and a predictor based on the principal component analysis (PCA) in- and out-of-sample in terms of both statistical and economic significance. This finding is robust to bonds with different ratings and maturities, and the data based on individual bond or index returns and with and without controlling for the return on Treasuries.

The sign of the predictive variables is consistent with the risk premium theory. Predictive variables capture the risk premia in corporate bond returns which increase with business, credit and interest rate risks. The slopes of these predictors increase from high-grade to low-grade bonds.

This pattern is in line with the intuition about the credit risk of bonds, that is, the sensitivity of bond returns to unexpected changes in business and credit risks increases as the bond rating decreases. Moreover, results show that the predictability of corporate bond risk premiums varies with economic conditions. Corporate bond returns are more predictable in a bad economy than in a good economy. Forecasts of the bond risk premium are strongly related to business cycles, consistent with the hypothesis that high risk aversion during economic recession requires a large compensation for risk bearing. Further analysis shows that the superior forecasting power of the RWC predictor is derived from its ability to predict future economic performance.

Stock and bond market variables contain useful information for predicting corporate bond returns. However, these variables must be carefully combined in order to preserve the valuable information in them for return forecasts. Improper use of these variables by a naive multiple regression or the principal component analysis destroys the value of these predictors. We show that the proposed regressed combination method is capable of extracting the useful information by reducing noise in individual predictors to obtain optimal forecasts. Using this method, we find that the true predictability of corporate bond returns is considerably understated if the predictors are restricted to only a few conventional variables. Results show that the expected returns of high-grade (low-grade) bonds are more closely related to the Treasury (stock) market variables, which is strongly consistent with the economic intuition that high-rated (low-rated) bonds behave more like Treasury bonds (stocks). In addition, macroeconomic variables, such as inflation rates, interest rates and liquidity factors, have predictive power for corporate bond returns. This finding is consistent with recent empirical and theoretical studies that macroeconomic factors contain important information for the term structure of bonds.

Our findings have important implications for corporate bond portfolio and risk management and the credit default swap (CDS) pricing, and it will be fruitful to explore these issues in future research. In addition, our proposed regressed combination approach can be an effective means for predicting the returns on other asset classes or wherever forecasting is of concern in finance or economics.

References

Acharya, Viral. V., and Lasse H. Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375–410.

Almeida, Caio, Jeremy J. Graveline, and Scott Joslin, 2011, Do interest rate options contain information about excess returns? *Journal of Econometrics* 164, 35–44.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Ang, Andrew, and Geert Bekaert, 2007, Stock return predictability: Is it there? *Review of Financial Studies* 20, 651–707.

Aruoba, S. Boraĝan, Francis X. Diebold, and Chiara Scotti, 2009, Real-time measurement of business conditions, *Journal of Business and Economic Statistics* 27, 417–427.

Baker, Malcolm, Robin Greenwood, and Jeffrey Wurgler, 2003, The maturity of debt issues and predictable variation in bond returns, *Journal of Financial Economics* 70, 261–291.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

Bates, J. M., and Clive M.J. Granger, 1969, The combination of forecasts, *Operations Research Quarterly* 20, 451–468.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring abnormal bond performance, *Review of Financial Studies* 22, 4219–4258.

Bharath, Sreedhar T., and Tyler Shumway, 2008, Forecasting default with the Merton distance to default model, *Review of Financial Studies* 21, 1339–1369.

Buraschi, Andrea, and Alexei Jiltsov, 2007, Habit formation and macroeconomic models of the term structure of interest rates, *Journal of Finance* 62, 3009-3063.

Buraschi, Andrea, and Davide Menini, 2002, Liquidity risk and specialness, *Journal of Financial Economics* 64, 243–284.

Campbell, John Y., and John H. Cochrane, 1999, By forces of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton University Press, Princeton, NJ).

Campbell, John Y., and Robert J. Shiller, 1988, Stock returns, earnings, and expected dividends, *Journal of Finance* 43, 661–676.

Campbell, John Y., and Robert J. Shiller, 1991, Yield spreads and interest rates: A bird's eye view, *Review of Economic Studies* 58, 495–514.

Campbell, John Y., and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies* 21, 1510–1531.

Campbell, John Y., and Tuomo Vuolteenaho, 2004. Inflation illusion and stock prices, *American Economic Review* 94, 19–23.

Capistrán, Carlos, and Allan Timmermann, 2009, Forecast combination with entry and exit of experts, *Journal of Business and Economic Statistics* 27, 428–440.

Chauvet, Marcelle, 1998, An economic characterization of business cycle dynamics with factor structure and regime switching, *International Economic Review* 39, 969–996.

Clark, Todd E., and Kenneth D. West, 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* 138, 291–311.

Cochrane, John H., and Monika Piazzesi, 2005, Bond risk premia, *American Economic Review* 95, 138–160.

Cochrane, John H., 2007, Financial markets and the real economy, In: Mehra, Rajnish (Ed.), *Handbook of the Equity Premium* (Elsevier, Amsterdam), 237–330.

Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spencer Martin, 2001, The determinants of credit spread changes, *Journal of Finance* 56, 2177–2207.

Dangl, Thomas, and Michael Halling, 2012, Predictive regressions with time-varying coefficients, *Journal of Financial Economics* 106, 157–181.

Duffie, Darrell, 1996, *Dynamic Asset Pricing Theory* (Princeton University Press, Princeton, NJ).

Fama, Eugene F., and Robert R. Bliss, 1987, The information in long-maturity forward rates, *American Economic Review* 77, 680–692.

Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and G. William Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 115–146.

Ferreira, Miguel A., and Pedro Santa-Clara, 2011, Forecasting stock market returns: The sum of the parts is more than the whole, *Journal of Financial Economics* 100, 514–537.

Gilchrist, Simon, and Egon Zakrajšek, 2012, Credit spreads and business cycle fluctuations, *American Economic Review* 102, 1692–1720.

Goetzmann,William, Jonathan Ingersoll, Matthew Spiegel, and Ivo Welch, 2007, Portfolio performance manipulation and manipulation-proof performance measures, *Review of Financial Studies* 20, 1503–1546.

Goh, Jeremy, Fuwei Jiang, Jun Tu, and Guofu Zhou, 2011, Predict bond risk premia using technical indicators, Working paper, Washington University at St. Louis.

Greenwood, Robin, and Samuel G. Hanson, 2013, Issuer quality and corporate bond returns, *Review of Financial Studies* 68, 1483–1525.

Gurkaynak, Refet S., Brian Sack, and Jonathan H. Wright, 2007, The U.S. Treasury yield curve: 1961 to the present, *Journal of Monetary Economics* 54, 2291-2304.

Harvey, David I., Stephen J. Leybourne, and Paul Newbold, 1998, Tests for forecast encompassing, *Journal of Business and Economics Statistics* 16, 254–259.

Hasbrouck, Joel, 2009, Trading costs and returns for US equities: Estimating effective costs from daily data, *Journal of Finance* 64, 1445–1477.

Henkel, Sam James, J. Spencer Martin, and Federico Nardari, 2011, Time-varying short-horizon predictability, *Journal of Financial Economics* 99, 560–580.

Hodrick, Robert J., 1992, Dividend yields and expected stock returns: Alternative procedures for inference and measurement, *Review of Financial Studies* 5, 357–386.

Huang, Dashan, Fuwei Jiang, Jun Tu, and Guofu Zhou, 2015, Investor sentiment aligned: A powerful predictor of stock returns, *Review of Financial Studies* 28, 791-837.

Jordan, Bradford D., and Susan D. Jordan, 1997, Special repo rates: An empirical analysis, *Journal of Finance* 52, 2051–2072.

Joslin, Scott, Marcel Priebsch, and Kenneth J. Singleton, 2014, Risk premiums in dynamic term structure models with unspanned macro risks, *Journal of Finance* 69, 1197-1234.

Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357–390.

Kelly, Bryan, and Seth Pruitt, 2013, Market expectations in the cross-section of present values, *Journal of Finance* 68, 1721–1757.

Kelly, Bryan, and Seth Pruitt, 2014, The three-pass regression filter: A new approach to forecasting using many predictors, *Journal of Econometrics*, forthcoming.

Kothari, S. P., and Jay Shanken, 1997, Book-to-market dividend yield, and expected market returns: A time-series analysis, *Journal of Financial Economics* 44, 169–203.

Krishnamurthy, Arvind, 2002, The bond/old-bond spread, *Journal of Financial Economics* 66, 463–506.

Lettau, Martin, and Sydney Ludvigson, 2001, Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815–849.

Lin, Hai, Junbo Wang, and Chunchi Wu, 2014, Predictions of corporate bond excess returns, *Journal of Financial Markets*, forthcoming.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market, *Journal of Finance* 60, 2213–2253.

Longstaff, Francis A., Jun Pan, Lasse H. Pedersen, and Kenneth J. Singleton, 2011, How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics* 3, 75–103.

Ludvigson, Sydney C., and Serena Ng, 2009, Macro factors in bond risk premia, *Review of Financial Studies* 22, 5027–5067.

Marquering, Wessel, and Marno Verbeek, 2004, The economic value of predicting stock index returns and volatility, *Journal of Financial and Quantitative Analysis* 39, 407–429.

Merton, Robert C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449–470.

Næs, Randi, Johannes A.Skjeltorp, and Bernt A. Ødegaard, 2011, Stock market liquidity and the business cycle, *Journal of Finance* 66, 139–176.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Pettenuzzo, Davide, Allan Timmermann, and Rossen Valkanov, 2014, Forecasting stock returns under economic constraints, *Journal of Financial Economics*, 114, 517–553.

Pflueger, Carolin E., and Luis M. Viceira, 2011, An empirical decomposition of risk and liquidity in nominal and inflation-indexed government bonds, Working paper, Harvard University.

Pontiff, Jeffrey, and Lawrence D. Schall, 1998, Book-to-market ratios as predictors of market returns, *Journal of Financial Economics* 49, 141–160.

Rapach, David E., Jack K. Strauss, and Guofu Zhou, 2010, Out-of-sample equity premium prediction: Combination forecast and links to the real economy, *Review of Financial Studies* 23, 821–862.

Remolona, Eli M., Michela Scatigna, and Eliza Wu, 2008, The dynamic pricing of sovereign risk in emerging markets: Fundamentals of risk aversion, *Journal of Fixed Income* 17, 57–71.

Stock, James H., and Mark W. Watson, 1999, Forecasting inflation, *Journal of Monetary Economics* 44, 293–335.

Stock, James H., and Mark W. Watson, 2001, A Comparison of linear and nonlinear univariate models for forecasting macroeconomic time series, In Engle, Robert F., and Halbert White

(Eds.), *Cointegration, Causality, and Forecasting: A Festschrift in Honour of Clive Granger* (Oxford University Press, Oxford), 1–44.

Thornton, Daniel L., and Giorgio Valente, 2012, Out-of-sample predictions of bond excess returns and forward rates: An asset-allocation perspective, *Review of Financial Studies* 25, 3141–3168.

Timmermann, Allan, 2006, Forecast combinations, In: Elliott, Graham, Clive W. J. Granger, and Allan Timmermann (Eds.), *Handbook of Economic Forecasting, Volume 1* (Elsevier, Amsterdam), 135–196.

Tu, Jun, and Guofu Zhou, 2011, Markowitz meets Talmud: A combination of sophisticated and naive diversification strategies, *Journal of Financial Economics* 99, 204–215.

Wachter, Jessica A., and Missaka Warusawitharana, 2009, Predictable returns and asset allocation: Should a skeptical investor time the market? *Journal of Econometrics* 148, 162–178.

Welch, Ivo, and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Whaley, Robert E., 2009, Understanding the VIX, *Journal of Portfolio Management* 35, 98–105.

Wold, Herman, 1966, Estimation of principal components and related models by iterative least squares, In: Krishnaiaah, P. R. (Ed.), *Multivariate Analysis* (Academic Press, New York), 391–420.

Zhou, Guofu, and Yingzi Zhu, 2015, Macroeconomic volatilities and the long-run risks of asset prices, *Management Science* 61, 413–430.

Table 1. Summary statistics of predictors

This table reports the summary statistics of the predictors: the dividend-price ratio (D/P), dividend yields (D/Y), the earnings-price ratio (E/P), the dividend-payout ratio (D/E), stock variance (SVAR), the book-to-market ratio (B/M), net equity expansion (NTIS), S&P 500 index return (S&P500), aggregate leverage ratios (LEV1 and LEV2), effective cost (EC), Pastor-Stambaugh stock liquidity (PSS), Amihud stock liquidity (AmS), Treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), inflation rate (INFL), CP 5-year factor (CP5), CP 10-year factor (CP10), percentage changes in the money market mutual fund flow (ΔMMMF), on-/off-the-run spread (Onoff), default yield spread (DFY), default return spread (DFR), issuance quality index (IQ), debt maturity index (DM) and portfolio yield spread (PYS) computed as the the mean yield spread of 20 corporate bond portfolios under investigation. ρ (1) and ρ (12) are the autoregressive coefficients at lag 1 and 12 of monthly intervals.

	Predictor	Obs.	Mean	Std.	ρ (1)	ρ (12)
Stock market variables	D/P	474	-3.60	0.45	0.99	0.92
	D/Y	474	-3.59	0.45	0.99	0.92
	E/P	474	-2.81	0.51	0.99	0.69
	D/E	474	-0.79	0.35	0.98	0.2
	SVAR (%)	474	0.26	0.51	0.46	0.03
	B/M (%)	474	50.11	29.8	0.99	0.93
	NTIS (%)	474	0.92	1.99	0.97	0.48
	S&P 500 (%)	474	0.89	4.56	0.04	0.07
	LEV1 (%)	474	38.41	4.05	0.96	0.55
	LEV2 (%)	474	43.47	6.52	0.98	0.75
	EC	396	-0.01	0.22	0.04	0.19
	PSS	474	0.00	0.06	0.00	-0.02
	AmS	456	0.00	0.21	-0.02	0.06
Treasury market variables	TBL (%)	474	5.37	3.30	0.99	0.84
	LTY (%)	474	7.43	2.59	0.99	0.90
	LTR (%)	474	0.77	3.16	0.05	0.00
	TMS (%)	474	2.07	1.54	0.95	0.48
	INFL (%)	474	0.36	0.38	0.62	0.46
	CP 5-year (%)	474	1.33	1.81	0.77	0.45
	CP 10-year (%)	474	1.92	4.01	0.90	0.50
	ΔMMMF (%)	463	2.00	5.04	0.69	0.23
	Onoff (Bps)	474	2.18	22.90	0.18	0.03
Corporate bond market variables	DFY (%)	474	1.12	0.48	0.96	0.44
	DFR (%)	474	-0.02	1.47	-0.04	-0.02
	IQ (%)	426	-25.49	21.29	0.97	0.41
	DM (%)	474	-61.43	7.40	0.99	0.96
	PYS (%)	474	3.04	1.65	0.81	0.37

Table 2. Sample distribution and summary statistics

This table reports the sample distribution of the corporate bond data (Panel A) and the summary statistics by rating and maturity (Pane B). The data are merged from different sources: the Lehman Brothers Fixed Income (LBFI) database, Datastream, the National Association of Insurance Commissioners (NAIC) database, the Trade Reporting and Compliance Engine (TRACE) database, and Mergent's Fixed Investment Securities Database (FISD). The combined corporate bond data are from January 1973 to June 2012. In each month, all bonds are sorted into five rating portfolios and then four maturity portfolios. The cut-off values for maturity portfolios are 5 years, 7 years, and 10 years.

Panel A. Sample distribution

Maturity	AAA	AA	A	BBB	Junk	All
			Distribution by maturity			
3	11,471	26,152	46,956	18,683	11,679	114,941
4	8,480	21,357	39,053	17,398	9,318	95,606
5	8,454	20,010	36,261	17,396	8,551	90,672
6	5,109	12,384	24,539	13,510	7,622	63,164
7	5,339	11,360	24,128	14,235	8,252	63,314
8	4,876	9,000	20,012	11,799	6,119	51,806
9	4,514	8,789	20,971	13,527	5,468	53,269
10	4,161	8,235	20,843	15,114	5,382	53,735
>10	11,818	25,981	70,031	62,598	24,050	194,478
All	64,222	143,268	302,794	184,260	86,441	780,985
			Distribution by data source			
Datastream	8,326	25,613	41,863	50,450	21,234	147,486
LBFI	15,539	42,180	115,257	65,312	23,533	261,821
NAIC	25,851	14,699	39,085	22,475	8,505	110,615
TRACE	14,506	60,776	106,589	46,023	33,169	261,063
All	64,222	143,268	302,794	184,260	86,441	780,985

Panel B. Summary statistics by rating and maturity

		Equal weighted			Value weighted		
Rating	Maturity	Excess return	S.D.	Corr. with equity	Excess return	S.D.	Corr. with equity
	All	0.26	1.84	0.25	0.26	1.73	0.22
AAA	Short	0.21	1.21	0.26	0.21	1.18	0.21
	Long	0.36	2.92	0.23	0.38	2.95	0.21
	All	0.27	1.76	0.33	0.26	1.68	0.31
AA	Short	0.24	1.24	0.33	0.21	1.19	0.31
	Long	0.40	2.54	0.29	0.39	2.55	0.27
	All	0.28	1.89	0.35	0.30	1.84	0.35
A	Short	0.25	1.38	0.34	0.24	1.36	0.33
	Long	0.40	2.64	0.33	0.41	2.64	0.34
	All	0.36	2.13	0.36	0.37	1.92	0.37
BBB	Short	0.31	1.73	0.34	0.33	1.54	0.35
	Long	0.45	2.90	0.32	0.39	2.89	0.34
	All	0.52	2.13	0.44	0.62	2.30	0.45
Junk	Short	0.35	2.16	0.34	0.48	2.29	0.38
	Long	0.75	2.67	0.44	0.90	3.19	0.41
	All	0.32	1.81	0.37	0.31	1.63	0.32
All	Short	0.27	1.31	0.36	0.25	1.15	0.30
	Long	0.45	2.50	0.35	0.44	2.31	0.30

Table 3. In-sample R-squares of individual predictors and covariance of predictors with corporate bond excess returns

This table reports the in-sample univariate regression R-squares of various predictors (the left panel), and estimates of the covariances of standardized individual predictors with the excess returns of rating portfolios (the right panel). The boldfaced figures indicate significance at least at the 10% level.

	In-sample R-squares of individual predictors												Covariance of predictors with corporate bond excess returns											
	Monthly (%)						Quarterly (%)						Monthly (%)						Quarterly (%)					
Predictor	AAA	AA	A	BBB	Junk	All	AAA	AA	A	BBB	Junk	All	AAA	AA	A	BBB	Junk	All	AAA	AA	A	BBB	Junk	All
D/P	0.10	0.19	0.00	0.05	0.01	0.07	0.33	0.42	0.00	0.07	0.06	0.20	-0.05	-0.07	-0.01	-0.04	0.03	-0.04	-0.06	-0.07	0.00	-0.03	0.03	-0.04
D/Y	0.21	0.26	0.00	0.02	0.04	0.13	0.55	0.61	0.01	0.09	0.04	0.33	-0.07	-0.08	-0.01	-0.02	0.04	-0.05	-0.08	**-0.08**	-0.01	-0.04	0.03	-0.06
E/P	0.23	1.80	1.23	1.83	2.48	0.60	0.48	3.67	2.36	3.51	3.98	1.19	-0.08	**-0.20**	**-0.18**	**-0.24**	**-0.33**	**-0.12**	-0.07	**-0.20**	**-0.18**	**-0.23**	**-0.28**	**-0.11**
D/E	0.09	1.80	2.25	2.66	5.67	0.59	0.08	3.64	4.66	5.46	10.20	1.05	**0.05**	**0.20**	**0.25**	**0.29**	**0.51**	**0.12**	0.03	**0.20**	**0.25**	**0.29**	**0.45**	**0.10**
SVAR	1.36	2.16	1.94	1.05	1.21	1.34	2.19	5.77	4.19	3.58	4.55	2.97	**0.19**	**0.22**	**0.23**	**0.18**	**0.23**	**0.17**	**0.16**	**0.25**	**0.24**	**0.23**	**0.30**	**0.17**
B/M	0.24	0.61	0.18	0.39	0.25	0.35	0.59	1.26	0.29	0.71	0.41	0.74	-0.08	**-0.12**	-0.07	-0.11	-0.11	-0.09	**-0.08**	**-0.12**	-0.06	**-0.10**	-0.09	**-0.09**
NTIS	1.12	0.65	0.52	0.21	0.50	0.83	2.08	1.26	0.59	0.39	0.59	1.45	**-0.17**	**-0.12**	-0.12	-0.08	-0.15	**-0.14**	**-0.15**	**-0.12**	**-0.09**	**-0.08**	**-0.11**	**-0.12**
S&P 500	1.74	0.45	0.00	0.86	0.74	0.64	2.77	1.38	0.52	0.02	0.04	1.54	**-0.21**	-0.10	0.00	**0.17**	**0.18**	**-0.12**	**-0.18**	**-0.12**	-0.08	-0.02	-0.03	**-0.13**
LEV1	0.28	0.94	1.04	0.67	1.56	0.44	0.20	1.67	2.15	1.69	3.14	0.63	0.09	**0.15**	**0.17**	**0.15**	**0.27**	0.10	0.05	**0.13**	**0.17**	**0.16**	**0.25**	**0.08**
LEV2	1.85	3.21	3.01	3.90	5.60	2.74	3.06	5.92	5.09	8.15	10.47	5.14	**0.22**	**0.27**	**0.29**	**0.35**	**0.50**	**0.25**	**0.19**	**0.25**	**0.27**	**0.35**	**0.46**	**0.23**
EC	0.49	0.85	0.80	0.45	1.21	0.64	0.35	0.87	0.76	0.72	1.30	0.61	0.12	**0.14**	**0.15**	0.11	**0.21**	0.12	0.07	**0.10**	**0.10**	**0.10**	**0.15**	0.08
PSS	0.01	0.39	0.29	0.84	0.93	0.23	0.40	0.14	0.09	0.03	0.06	0.17	-0.02	-0.09	-0.09	**-0.16**	**-0.21**	-0.07	0.07	0.04	0.04	-0.02	0.03	0.04
AmS	0.13	0.25	0.34	0.00	0.01	0.11	1.14	0.59	0.43	0.07	0.22	0.70	0.06	0.08	0.10	0.00	-0.03	0.05	**0.11**	0.08	0.08	0.03	0.07	**0.09**
TBL	0.76	1.72	1.16	2.47	2.56	1.42	0.99	2.63	1.51	3.98	3.94	2.07	**-0.14**	**-0.20**	**-0.18**	**-0.28**	**-0.34**	**-0.18**	**-0.11**	**-0.17**	**-0.14**	**-0.25**	**-0.28**	**-0.15**
LTY	0.09	0.30	0.05	0.37	0.61	0.18	0.00	0.15	0.01	0.24	0.49	0.03	-0.05	-0.08	-0.04	-0.11	**-0.17**	-0.06	0.00	-0.04	0.01	-0.06	-0.10	-0.02
LTR	5.29	4.53	4.47	5.95	4.27	5.83	0.65	0.74	0.52	1.04	0.76	1.14	**0.37**	**0.32**	**0.35**	**0.44**	**0.44**	**0.36**	**0.09**	**0.09**	**0.09**	**0.13**	**0.12**	**0.11**
TMS	1.95	3.67	3.82	5.61	4.61	3.47	4.83	8.15	7.94	12.05	9.60	7.94	**0.23**	**0.29**	**0.32**	**0.42**	**0.46**	**0.28**	**0.23**	**0.29**	**0.33**	**0.43**	**0.44**	**0.28**
INFL	0.76	2.30	1.52	2.27	2.55	1.97	0.54	2.68	1.87	2.63	4.32	1.95	**-0.14**	**-0.23**	**-0.20**	**-0.27**	**-0.34**	**-0.21**	**-0.08**	**-0.17**	**-0.16**	**-0.20**	**-0.29**	**-0.14**
CP5	1.17	2.02	2.37	2.65	1.61	1.97	3.56	5.25	5.52	6.06	4.77	5.68	**0.18**	**0.21**	**0.25**	**0.29**	**0.27**	**0.21**	**0.20**	**0.24**	**0.28**	**0.30**	**0.31**	**0.24**
CP10	2.32	3.30	2.92	2.93	2.17	3.23	6.25	6.98	6.36	6.18	4.87	7.83	**0.25**	**0.27**	**0.28**	**0.31**	**0.31**	**0.27**	**0.27**	**0.27**	**0.30**	**0.31**	**0.31**	**0.28**
ΔMMMF	1.24	2.10	2.55	3.06	1.79	2.10	1.73	3.28	3.96	4.92	3.23	3.14	**-0.18**	**-0.22**	**-0.26**	**-0.31**	**-0.29**	**-0.22**	**-0.14**	**-0.19**	**-0.23**	**-0.28**	**-0.26**	**-0.18**
Onoff	5.60	5.95	5.85	6.11	5.94	6.70	1.61	2.46	2.09	2.97	2.89	2.85	**0.38**	**0.37**	**0.40**	**0.44**	**0.52**	**0.39**	**0.13**	**0.16**	**0.17**	**0.21**	**0.24**	**0.17**
DFY	0.23	1.23	2.03	2.38	2.41	0.89	0.18	2.08	3.52	4.10	3.65	1.18	0.08	**0.17**	**0.23**	**0.28**	**0.33**	**0.14**	0.04	**0.15**	**0.22**	**0.25**	**0.27**	**0.11**
DFR	0.91	0.03	0.01	0.59	0.13	0.28	0.38	0.04	0.00	0.21	0.37	0.14	**-0.15**	-0.03	-0.02	**0.14**	0.08	-0.08	-0.07	-0.02	0.00	0.06	0.09	-0.04
IQ	0.00	0.14	0.32	0.16	0.43	0.03	0.01	0.29	0.68	0.33	0.97	0.05	0.00	0.06	0.10	0.07	0.14	0.02	-0.01	0.06	0.10	0.07	**0.14**	0.02
DM	0.12	0.34	0.21	0.87	0.89	0.23	0.14	0.47	0.21	1.39	1.25	0.31	-0.06	-0.09	-0.08	**-0.17**	**-0.20**	-0.07	-0.04	-0.07	-0.05	**-0.15**	**-0.16**	-0.06
PYS	0.75	2.79	3.28	5.18	6.88	2.91	3.57	9.41	10.58	14.78	15.80	8.95	**0.14**	**0.25**	**0.30**	**0.41**	**0.56**	**0.26**	**0.20**	**0.32**	**0.38**	**0.48**	**0.57**	**0.30**

Table 4. In-sample R-squares

The left panel reports the in-sample R-squares of combination and regressed combination forecasts, including the mean combination (MC), the median combination (MD), the trimmed mean combination (TC), the weighted-average combination (WC) and their regressed combination forecast. The right panel reports the in-sample R-squares of the PCA, the Fama-French (1989, FF) model and the Greenwood-Hanson (2013, GH) model at the monthly horizon and for the four models including RWC at the quarterly horizon. Δ is the difference between in-sample R-squares of the RWC and FF models.

		Combination forecast versus regressed combination forecast								Other predictors and comparison								
		Combination forecast (%)				Regressed combination forecast (%)				Monthly(%)				Quarterly(%)				
		MC	MD	TC	WC	RMC	RMD	RTC	RWC	PCA	FF	GH	Δ	RWC	PCA	FF	GH	Δ
All	AAA	2.06	0.99	1.79	2.07	9.28	5.27	8.49	9.46	0.20	2.06	0.73	7.40	11.73	0.41	4.85	3.49	6.88
	AA	3.04	1.64	2.77	3.04	11.18	6.57	10.55	11.30	0.44	4.48	2.72	6.82	17.13	0.86	9.40	6.88	7.73
	A	2.93	1.27	2.62	2.93	11.33	9.13	10.72	11.46	0.07	5.28	3.59	6.18	16.59	0.11	10.38	8.53	6.21
	BBB	3.71	1.73	3.41	3.70	13.40	8.34	12.82	13.52	0.26	7.25	5.04	6.27	19.44	0.56	14.72	11.38	4.72
	Junk	3.95	2.12	3.53	3.90	14.03	11.06	13.04	14.11	0.17	6.33	4.73	7.78	21.17	0.36	12.04	9.51	9.13
	ALL	2.76	1.25	2.44	2.79	11.01	5.72	10.12	11.22	0.25	4.00	2.35	7.22	15.64	0.47	8.52	6.34	7.12
Short (2 Yrs Mat. <5 Yrs)	AAA	2.46	0.96	2.08	2.53	12.38	9.42	11.38	12.72	0.01	2.28	1.11	10.44	13.71	0.01	4.42	4.04	9.29
	AA	3.54	1.65	3.17	3.56	14.14	8.81	13.41	14.40	0.25	4.99	3.58	9.41	20.29	0.37	9.76	8.00	10.53
	A	3.41	1.30	3.03	3.41	14.22	11.49	13.58	14.41	0.00	5.99	4.78	8.42	19.27	0.01	10.33	9.28	8.94
	BBB	3.86	1.94	3.52	3.84	15.00	11.20	14.47	15.20	0.05	7.62	5.88	7.58	20.35	0.05	13.81	10.90	6.54
	Junk	3.49	2.03	3.10	3.43	12.96	10.68	12.24	13.02	0.11	5.80	4.32	7.22	18.32	0.17	8.99	6.83	9.33
	All	3.12	1.22	2.71	3.18	13.92	8.59	12.77	14.31	0.07	4.27	2.77	10.04	17.75	0.11	7.85	6.18	9.90
5.00 Yrs < Mat. < 7.00 Yrs.	AAA	2.43	0.86	2.02	2.47	11.93	6.44	10.47	12.21	0.02	1.73	0.78	10.48	13.34	0.01	3.78	3.17	9.56
	AA	3.03	1.59	2.72	3.03	11.44	6.66	10.61	11.65	0.38	3.89	2.22	7.76	16.04	0.71	7.94	5.59	8.10
	A	3.23	1.37	2.86	3.22	12.67	9.78	11.84	12.85	0.06	5.30	3.94	7.55	16.91	0.06	9.36	7.93	7.55
	BBB	3.06	1.36	2.78	3.06	11.73	6.47	11.02	11.84	0.17	5.65	3.97	6.19	17.67	0.49	12.78	9.88	4.89
	Junk	2.74	1.26	2.46	2.72	10.21	6.64	9.52	10.32	0.06	4.16	2.62	6.16	19.89	0.13	12.76	10.75	7.13
	All	2.72	1.17	2.39	2.75	11.30	5.95	10.33	11.61	0.16	3.76	2.37	7.85	15.68	0.39	8.10	6.34	7.58
7.00 Yrs < Mat. < 10Yrs	AAA	1.75	0.79	1.48	1.76	8.08	3.85	7.25	8.25	0.13	1.37	0.23	6.88	9.71	0.74	4.12	3.20	5.59
	AA	2.79	1.42	2.52	2.79	10.43	5.66	9.70	10.57	0.35	3.81	2.18	6.76	15.38	0.71	8.24	6.23	7.14
	A	2.73	1.07	2.42	2.73	10.63	7.55	9.89	10.74	0.05	5.05	3.35	5.69	15.80	0.06	10.60	8.92	5.20
	BBB	3.23	1.38	2.90	3.24	12.03	9.34	11.39	12.15	0.06	7.24	5.36	4.91	18.39	0.10	14.88	12.45	3.51
	Junk	3.35	1.61	3.04	3.34	10.92	6.41	10.00	11.00	0.58	4.38	3.18	6.62	18.37	0.81	10.77	8.90	7.60
	All	2.51	1.01	2.21	2.52	9.95	4.69	9.15	10.12	0.15	3.83	2.30	6.29	15.00	0.38	8.66	6.78	6.34
Long (Mat. >10 Yrs)	AAA	1.62	0.65	1.42	1.61	7.27	3.74	6.61	7.33	0.16	1.99	0.63	5.34	10.95	0.81	6.71	4.94	4.24
	AA	2.38	1.32	2.19	2.35	7.91	4.47	7.47	7.94	0.64	3.61	1.79	4.33	14.26	1.43	8.47	5.83	5.79
	A	2.24	0.92	1.97	2.23	7.83	4.73	7.03	7.86	0.20	4.51	2.68	3.35	14.71	0.60	11.18	8.39	3.53
	BBB	2.88	1.42	2.68	2.87	9.81	5.52	9.42	9.90	0.55	5.45	3.75	4.45	16.88	1.63	13.47	10.97	3.41
	Junk	2.66	1.02	2.26	2.63	9.83	5.08	8.68	9.77	0.01	4.79	2.88	4.98	19.18	0.00	10.49	8.31	8.69
	All	2.42	0.95	2.11	2.43	9.28	3.81	8.35	9.39	0.26	3.60	1.83	5.79	15.25	0.87	10.01	7.42	5.24
Average		2.87	1.31	2.55	2.87	11.20	7.10	10.41	11.35	0.20	4.48	2.92	6.87	16.49	0.45	9.58	7.58	6.91

Table 5. Out-of-sample R-squares

The left panel reports the monthly out-of-sample R-squares of the four combination forecasts and their regressed combination forecasts. The right panel reports the out-of-sample R-squares of the PCA, the Fama-French (1989, FF) model and the Greenwood-Hanson (2013, GH) model at the monthly horizon and the four models including the RWC at the quarterly horizon. The p-value is based on the MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance levels of 1%, 5%, and 10%, respectively. Δ is the difference between out-of-sample R-squares of the RWC and FF forecasts.

		Combination forecast versus regressed combination forecast								Other predictors and comparison								
		Combination forecast (%)				Regressed combination forecast (%)				Monthly(%)				Quarterly(%)				
		MC	MD	TC	WC	RMC	RMD	RTC	RWC	PCA	FF	GH	Δ	RWC	PCA	FF	GH	Δ
All	AAA	2.18^a	1.1^a	1.82^a	2.21^a	5.21^a	5.6^a	4.52^a	5.32^a	-0.47	1.6^a	0.71^b	3.72	5.73^b	-1.67	3.37^a	1.05	2.36
	AA	3.46^a	1.84^a	3.02^a	3.49^a	9.88^a	8.58^a	9.09^a	9.93^a	0.15	5.52^a	2.79^a	4.41	15.6^a	-0.58	10.41^a	5.63^b	5.19
	A	2.63^a	1.14^a	2.29^a	2.67^a	8.55^a	7.55^a	8.12^a	8.56^a	-1.38	4.86^a	1.40^b	3.70	11.3^a	-3.08	9.24^a	4.40^c	2.06
	BBB	3^a	1.24^a	2.7^a	3.05^a	9.58^a	6.71^a	9.63^a	9.68^a	-0.7	5.99^a	1.51^b	3.69	15.27^a	-2.06	13.42^a	6.56^c	1.85
	Junk	2.97^a	1.11^a	2.51^a	3.03^a	11.22^a	7.72^a	10.94^a	11.34^a	-0.68	5.72^a	3.03^a	5.62	16.98^a	-2.54	10.31^a	3.91^b	6.67
	All	2.92^a	1.44^a	2.55^a	2.96^a	7.7^a	6.78^a	7.1^a	7.82^a	-1.32	3.58^a	0.72^b	4.24	12.07^a	-2.83	7.28^a	3.11^b	4.79
Short (2 Yrs < Mat. <5 Yrs)	AAA	2.8^a	1.16^a	2.23^a	2.87^a	4.46^a	5.01^a	3.34^a	4.67^a	-2.32	1.14^a	0.41^b	3.53	5.7^a	-5.04	2.44^b	0.93	3.26
	AA	4.03^a	1.92^a	3.43^a	4.09^a	11.88^a	11.11^a	10.7^a	11.98^a	-1.19	5.94^a	3.25^a	6.04	17.68^a	-3.74	10.46^a	6.00^b	7.22
	A	3.02^a	1.28^a	2.55^a	3.07^a	10.81^a	6.75^a	10.11^a	10.83^a	-2.22	5.47^a	2.65^b	5.36	13.08^b	-4.85	9.16^a	5.54^c	3.92
	BBB	3.12^a	1.51^a	2.78^a	3.18^a	11.24^a	9.95^a	11.31^a	11.24^a	-1.37	6.39^a	2.14^c	4.85	14.96^b	-4.18	12.14^b	4.34^c	2.82
	Junk	2.32^a	0.92^a	1.93^a	2.37^a	8.91^a	5.17^a	8.87^a	8.86^a	-0.55	5.42^a	3.39^b	3.44	10.32^b	-1.64	7.45^a	2.32^b	2.87
5 Yrs < Mat. < 7 Yrs.	All	3.15^a	1.37^a	2.68^a	3.23^a	7.19^a	5.2^a	6.41^a	7.41^a	-2.78	2.98^a	0.08^b	4.43	11.2^a	-6.68	5.41^a	2.13^b	5.79
	AAA	1.86^a	0.99^a	1.62^a	1.89^a	5.1^a	5.1^a	4.69^a	5.25^a	-0.69	0.55^c	-0.54	4.70	5.35^c	-2.65	0.82^a	-1.99	4.53
	AA	3.08^a	1.54^a	2.68^a	3.12^a	8.69^a	7.34^a	7.96^a	8.7^a	0.55	4.91^a	2.55^b	3.79	13.77^a	0.34	9.14^b	4.76	4.63
	A	2.61^a	1.06^a	2.2^a	2.64^a	8.4^a	7.19^a	8.17^a	8.38^a	-1.01	5.03^a	2.32^c	3.35	11.36^b	-2.58	8.71^a	4.81	2.65
	BBB	2.34^a	0.96^a	2.15^a	2.37^a	6.48^a	3.53^a	6.62^a	6.49^a	0.06	3.8^a	0.15	2.69	12.94^a	-0.54	10.22^a	3.65	2.72
	Junk	2.09^a	0.74^a	1.81^a	2.12^a	6.27^a	4.38^a	6.46^a	6.28^a	-0.54	3.13^a	0.63^c	3.15	12.73^a	-1.55	6.87^a	1.81^c	5.86
	All	2.67^a	1.22^a	2.3^a	2.72^a	6.9^a	5.94^a	6.17^a	7.05^a	-1.32	3.03^a	0.52^b	4.02	12.76^a	-3.33	7.18^a	3.36^c	5.58
7 Yrs < Mat. < 10Yrs	AAA	1.88^a	0.94^a	1.55^a	1.91^a	3.16^a	3.82^a	2.39^a	3.27^a	-0.71	0.99^c	0.16	2.28	3.77^b	-0.57	3.07^a	2.18^b	0.70
	AA	3.03^a	1.64^a	2.67^a	3.06^a	8.22^a	8.48^a	7.75^a	8.26^a	0.15^c	4.82^a	2.06^b	3.44	12.75^a	-0.61	9.12^a	4.32^c	3.63
	A	2.58^a	1.06^a	2.28^a	2.61^a	7.42^a	6.39^a	7.25^a	7.44^a	-1.11	5.06^a	1.25^c	2.38	10.81^a	-2.6	9.7^a	4.59^c	1.11
	BBB	3.09^a	1.18^a	2.75^a	3.15^a	8.14^a	6.56^a	8.22^a	8.29^a	-0.85	7.3^a	2.30^b	0.99	15.09^a	-2.12	15.5^a	8.86^b	-0.41
	Junk	3.08^a	1.25^a	2.7^a	3.13^a	8.86^a	5.51^a	8.78^a	9.02^a	0.35	3.81^a	0.72^b	5.21	13.1^a	-1.24	9.93^a	3.13^a	3.17
	All	2.78^a	1.16^a	2.43^a	2.82^a	7.09^a	5.54^a	6.65^a	7.17^a	-1.19	4.17^a	1.35^b	3.00	13^a	-2.89	9.38^a	3.46^a	3.62
Long (Mat. >10 Yrs)	AAA	1.36^a	0.63^a	1.18^a	1.37^a	2.11^a	2.02^a	2.37^a	2.1^a	-0.28	1.49^b	-0.39	0.61	3.72^b	0.83	5.93^a	-0.34	-2.21
	AA	2.38^a	1.21^a	2.1^a	2.39^a	5.66^a	5.31^a	5.45^a	5.72^a	0.71^b	4.11^a	1.71^b	1.61	11.58^a	0.85	8.58^a	2.99^c	3.00
	A	2.03^a	0.87^a	1.82^a	2.04^a	4.88^a	5.08^a	4.74^a	4.92^a	-0.27	4^a	0.91^b	0.92	10.37^a	-0.7	10.12^a	3.77^b	0.25
	BBB	2.49^a	1.08^a	2.31^a	2.51^a	5.77^a	4.74^a	5.96^a	5.77^a	0.87^b	4.04^a	1.76^b	1.73	12.49^a	2.76^b	9.29^a	5.41^b	3.20
	Junk	1.82^a	0.59^a	1.48^a	1.86^a	6.59^a	3.23^a	6.24^a	6.78^a	-0.97	3.7^a	0.35^b	3.08	12.3^a	-2.72	7.11^a	0.24^b	5.19
	All	2.29^a	1^a	2.01^a	2.33^a	5.41^a	4.04^a	4.99^a	5.49^a	-1.12	2.99^a	-0.02	2.50	10.83^a	-2.22	8.8^a	2.35^c	2.03
Average		2.63	1.17	2.28	2.67	7.39	6.01	7.03	7.47	-0.74	4.05	1.33	3.42	11.62	-2.01	8.35	3.44	3.27

Table 6. Utility gains
This table reports the annualized utility gains of the RWC, the PCA, the Fama-French (1989, FF) model and the Greenwood-Hanson (2013, GH) model. Δ is the difference between the utility gains of the RWC and FF models.

		Monthly(%)					Quarterly(%)				
Maturity	Rating	RWC	PCA	FF	GH	Δ	RWC	PCA	FF	GH	Δ
All	AAA	6.10	-0.53	1.37	0.16	4.73	2.46	-0.74	1.75	0.01	0.72
	AA	6.04	-0.28	2.33	-0.10	3.71	4.25	-0.53	2.89	1.65	1.35
	A	5.94	-1.86	1.74	-1.11	4.20	3.04	-1.79	1.47	1.11	1.57
	BBB	6.15	-1.73	1.31	-2.56	4.84	1.84	-1.73	0.82	-2.21	1.03
	Junk	2.35	-1.73	-1.77	-3.69	4.12	1.13	-1.95	0.55	0.50	0.58
	All	5.74	-1.41	1.58	-0.38	4.16	3.77	-1.46	1.86	0.37	1.91
Short (2 Yrs < Mat. <5 Yrs)	AAA	2.28	-2.90	-0.77	-0.38	3.05	0.69	-2.24	0.17	-0.67	0.51
	AA	4.32	-1.67	0.51	-0.35	3.81	3.46	-1.46	1.81	0.79	1.66
	A	3.54	-3.06	0.62	-1.02	2.92	2.27	-2.87	0.36	0.30	1.91
	BBB	6.90	-2.36	1.14	-1.70	5.76	1.12	-3.12	-0.61	-3.35	1.73
	Junk	4.28	-0.85	2.94	1.23	1.34	3.73	-0.76	3.10	2.28	0.62
	All	2.86	-3.16	-0.85	-1.48	3.71	1.42	-2.81	-0.41	-1.06	1.83
5 Yrs< Mat. < 7 Yrs	AAA	5.15	-1.43	-1.58	-1.63	6.73	0.48	-1.41	-1.60	-0.80	2.08
	AA	5.78	-0.10	1.75	-0.98	4.03	3.54	-0.31	2.41	1.41	1.12
	A	3.28	-1.79	-0.53	-2.80	3.81	0.96	-1.67	0.43	1.40	0.53
	BBB	4.81	-0.95	-1.56	-4.75	6.37	0.24	-1.14	-0.97	-4.01	1.20
	Junk	2.23	-0.74	-1.11	-4.70	3.34	2.78	-0.98	1.08	-1.34	1.70
	All	4.97	-1.73	1.05	-0.69	3.92	3.23	-1.51	1.30	-0.08	1.94
7 Yrs < Mat. < 10 Yrs	AAA	5.11	-0.94	-0.36	-0.56	5.47	2.15	-0.29	1.09	0.87	1.06
	AA	7.66	-0.32	2.11	-0.98	5.55	3.84	-0.58	2.42	1.23	1.42
	A	5.74	-1.56	-0.29	-3.47	6.03	2.54	-1.47	0.53	1.06	2.01
	BBB	6.49	-1.44	2.73	-0.83	3.76	2.53	-1.46	1.52	-1.02	1.00
	Junk	5.78	-0.22	-1.72	-7.12	7.50	1.22	-0.94	-0.60	-5.19	1.82
	All	6.93	-1.37	2.06	-0.43	4.87	4.31	-1.16	2.56	1.04	1.75
Long (Mat. > 10 Yrs)	AAA	2.82	-0.67	-0.51	-2.30	3.33	0.91	-0.23	1.55	-0.36	-0.64
	AA	4.00	-0.06	1.46	-1.75	2.54	2.25	-0.28	2.39	1.26	-0.15
	A	2.80	-0.92	-0.82	-3.00	3.62	0.55	-0.95	1.18	0.34	-0.63
	BBB	3.60	0.15	-0.27	-4.11	3.87	-0.07	0.43	1.57	-2.00	-1.64
	Junk	-0.60	-0.78	-4.35	-0.70	3.75	1.85	-1.00	-2.70	2.22	4.55
	All	6.42	-1.43	1.33	-2.54	5.09	3.87	-1.08	2.24	0.14	1.63
Average		4.65	-1.26	0.32	-1.82	4.33	2.21	-1.25	1.01	-0.14	1.21

Table 7. Forecast encompassing tests
This table reports the p-values of the Harvey, Leybourne and Newbold (1998) statistics for the null hypothesis that the out-of-sample forecast of model 1 encompasses the out-of-sample forecast of model 2 for bonds of different ratings and maturities.

			Rating					
Maturity	Model 1	Model 2	AAA	AA	A	BBB	Junk	All
All	RWC	FF	0.23	0.33	0.42	0.38	0.51	0.33
	RWC	GH	0.38	0.51	0.71	0.68	0.45	0.74
	RWC	PCA	0.15	0.38	0.49	0.33	0.53	0.23
	FF	RWC	0.00	0.00	0.00	0.00	0.00	0.00
	GH	RWC	0.00	0.00	0.00	0.00	0.00	0.00
	PCA	RWC	0.00	0.00	0.00	0.00	0.00	0.00
Short (2 Yrs < Mat. < 5 Yrs.)	RWC	FF	0.05	0.20	0.43	0.48	0.31	0.12
	RWC	GH	0.25	0.63	0.75	0.85	0.29	0.60
	RWC	PCA	0.04	0.22	0.54	0.44	0.47	0.07
	FF	RWC	0.00	0.00	0.00	0.00	0.00	0.00
	GH	RWC	0.00	0.00	0.00	0.00	0.02	0.00
	PCA	RWC	0.00	0.00	0.00	0.00	0.00	0.00
	MC	RWC	0.00	0.00	0.00	0.00	0.00	0.00
5 Yrs < Mat. < 7 Yrs.	RWC	FF	0.33	0.17	0.32	0.15	0.30	0.23
	RWC	GH	0.34	0.29	0.52	0.36	0.28	0.61
	RWC	PCA	0.17	0.24	0.43	0.08	0.22	0.17
	FF	RWC	0.00	0.00	0.01	0.00	0.00	0.00
	GH	RWC	0.00	0.00	0.01	0.00	0.00	0.00
	PCA	RWC	0.00	0.00	0.00	0.00	0.00	0.00
7 Yrs < Mat. < 10 Yrs.	RWC	FF	0.08	0.18	0.22	0.05	0.52	0.19
	RWC	GH	0.08	0.32	0.40	0.30	0.87	0.42
	RWC	PCA	0.08	0.23	0.31	0.13	0.38	0.20
	FF	RWC	0.00	0.00	0.00	0.01	0.00	0.00
	GH	RWC	0.00	0.00	0.00	0.00	0.00	0.00
	PCA	RWC	0.00	0.00	0.00	0.00	0.00	0.00
Long (Mat. > 10 Yrs.)	RWC	FF	0.11	0.17	0.18	0.14	0.44	0.23
	RWC	GH	0.14	0.08	0.26	0.04	0.48	0.43
	RWC	PCA	0.14	0.26	0.29	0.08	0.59	0.19
	FF	RWC	0.03	0.01	0.03	0.01	0.01	0.00
	GH	RWC	0.02	0.01	0.02	0.05	0.02	0.00
	PCA	RWC	0.00	0.00	0.00	0.00	0.00	0.00

Table 8. Out-of-sample forecasts using the RWC of Treasury market variables

This table reports the out-of-sample R-squares (R^2_{OS}) of regressed weighted average combination (RWC) forecast using only Treasury market variables for each portfolio formed by the rating, beta and EDF. The percentage measure is the ratio between the out-of-sample R-squares of the RWC using Treasury market variables only and that of the RWC using all variables including the Treasury, corporate bond and stock market variables. Beta is the stock market return beta and EDF is the expected default probability estimated from the Merton (1974) model. The statistical significance of R^2_{OS} is based on the p-value of the out-of-sample MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance level of 1%, 5%, and 10%, respectively.

		Monthly		Quarterly	
		R^2_{OS}	Percentage	R^2_{OS}	Percentage
Rating	AAA	5.76^a	108.36	3.57^b	62.33
	AA	8.10^a	81.53	9.59^a	61.49
	A	6.28^a	73.34	5.77^a	51.06
	BBB	6.64^a	68.62	7.19^a	47.08
	Junk	6.24^a	55.03	5.91^b	34.81
Beta	Low	8.23^a	102.99	6.54^a	59.66
	2	5.00^a	101.27	0.94^b	42.20
	3	6.25^a	100.17	3.90^b	39.57
	4	5.27^a	70.27	5.28^a	39.19
	High	2.91^a	48.74	3.36^b	36.47
EDF	Low	5.11^a	112.22	4.60^b	56.99
	2	7.64^a	83.78	6.73^b	43.84
	3	9.24^a	66.47	9.15^a	50.16
	4	4.93^a	69.73	3.25^b	50.47
	High	8.44^a	69.20	7.44^a	43.28

Table 9. Forecasts at longer horizons

This table reports the results of longer horizon forecasts over two quarters, three quarters and one year using the Fama-French (1989) model and the regressed weighted-average combination (RWC) method for junk-rated bonds. Δ is the difference between the results of of the RWC and FF models. The statistical significance of R^2_{OS} is based on the p-value of the out-of-sample MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance level of 1%, 5%, and 10%, respectively.

	Two quarter(%)			Three quarter(%)			One year(%)		
Maturity	FF	RWC	Δ	FF	RWC	Δ	FF	RWC	Δ
				In-sample R squares					
All	19.65	34.96	15.31	26.63	44.93	18.29	30.78	51.27	20.49
Short	17.20	33.81	16.61	22.69	41.97	19.28	26.35	48.50	22.15
5 Yrs<Mat<7 Yrs	20.50	33.95	13.45	27.04	43.37	16.33	29.73	49.28	19.55
7 Yrs<Mat<10 Yrs	15.55	28.64	13.09	21.09	37.32	16.23	24.91	43.91	19.00
Long	17.34	31.27	13.93	24.49	41.42	16.94	29.68	48.74	19.05
				Out-of-sample R squares					
All	15.88^a	23.51^a	7.63	21.73^a	24.78^b	3.05	26.46^a	28.05^b	1.59
Short	12.83^a	18.42^b	5.58	17.25^a	19.96^b	2.71	20.76^a	23.13^b	2.37
5 Yrs<Mat<7 Yrs	12.24^a	19.23^a	6.99	20.47^a	23.72^b	3.25	27.73^a	29.18^b	1.45
7 Yrs<Mat<10 Yrs	13.76^a	20.31^a	6.55	20.32^a	24.53^b	4.21	25.07^a	28.17^b	3.10
Long	11.75^a	17.08^a	5.32	17.67^a	20.54^a	2.87	21.46^a	24.89^b	3.43
				Utility gains					
All	-2.84	0.03	2.87	-2.48	0.72	3.20	-2.06	0.81	2.87
Short	0.52	3.55	3.03	0.45	2.81	2.36	0.63	2.51	1.87
5 Yrs<Mat<7 Yrs	-0.51	2.62	3.13	1.27	2.90	1.63	2.67	2.61	-0.06
7 Yrs<Mat<10 Yrs	-1.26	-0.38	0.88	-1.69	-0.44	1.25	-0.19	0.27	0.46
Long	-2.52	2.08	4.60	-1.00	2.69	3.69	-0.16	2.74	2.89

Table 10. Comparisons between the RWC and multiple regression models

This table reports the difference between the results of the regressed weighted combination (RWC) and multiple regression models. We consider four multiple regression models: (1) the multiple regression model using stock market variables; (2) the model using Treasury market variables; (3) the model using corporate bond market variables; and (4) the kitchen sink model using all variables. Δ1, Δ2, Δ3, Δ4 measure the difference of out-of-sample R squares between the RWC and the above four models.

		Monthly(%)				Quarterly(%)			
Maturity	Rating	Δ1	Δ2	Δ3	Δ4	Δ1	Δ2	Δ3	Δ4
All	AAA	18.64	2.98	5.16	37.14	64.46	9.64	4.66	63.95
	AA	22.80	7.20	9.39	42.95	63.99	16.10	10.60	64.01
	A	17.51	7.15	9.33	31.94	55.14	12.60	10.30	56.56
	BBB	22.91	6.95	9.53	38.88	48.25	15.27	12.63	66.63
	Junk	21.77	10.35	8.88	34.73	30.77	17.49	8.69	35.58
	All	19.85	6.11	7.32	37.36	71.84	15.91	7.92	70.22
Short (2 Yrs < Mat. <5 Yrs)	AAA	13.52	2.29	6.20	32.52	68.57	8.73	7.00	77.26
	AA	19.07	9.21	11.94	37.37	60.80	17.53	14.19	77.11
	A	19.34	10.83	10.60	35.84	57.24	16.94	10.90	66.20
	BBB	17.70	10.06	10.40	31.36	35.72	17.02	14.09	60.40
	Junk	16.45	9.03	7.22	22.97	22.38	11.51	9.01	24.01
	All	17.32	7.06	8.24	35.47	70.66	16.73	9.85	75.56
5 Yrs< Mat. < 7 Yrs	AAA	13.52	1.75	3.64	23.64	67.09	7.02	6.41	72.64
	AA	17.11	8.11	7.57	30.07	61.94	15.59	9.25	70.25
	A	16.03	9.57	7.22	31.55	59.94	14.53	8.72	66.28
	BBB	20.37	8.39	5.57	43.31	64.48	17.39	7.09	81.02
	Junk	18.22	5.91	5.29	24.22	64.53	17.28	5.39	56.93
	All	18.72	7.10	6.03	35.53	77.52	18.09	7.29	76.89
7 Yrs < Mat. < 10 Yrs	AAA	19.49	1.34	2.03	31.63	76.16	9.36	-0.24	52.72
	AA	19.60	4.43	7.81	40.10	60.38	11.46	8.51	56.61
	A	16.94	5.03	8.09	32.58	63.72	11.55	8.40	65.54
	BBB	26.19	7.47	8.29	51.49	61.86	17.82	12.46	83.21
	Junk	24.60	4.76	7.73	43.37	33.25	14.53	7.23	56.51
	All	17.44	4.77	5.89	36.55	78.24	14.94	5.90	76.34
Long (Mat. > 10 Yrs)	AAA	12.80	4.49	2.06	27.50	52.01	6.05	3.04	53.22
	AA	19.51	3.42	5.39	38.63	64.12	12.60	7.21	51.09
	A	13.64	5.38	5.98	23.22	51.25	8.49	8.46	52.81
	BBB	19.25	17.09	4.10	46.60	66.70	24.31	8.13	91.04
	Junk	16.37	8.06	5.84	27.06	22.30	11.48	6.34	35.79
	All	21.37	4.55	5.36	39.71	67.34	10.59	7.23	56.48
Average		18.60	6.69	6.94	34.84	59.09	13.95	8.22	70.58

Table 11. Forecasts of hedged returns and Barclays corporate bond index excess returns

This table reports the results of hedged returns and Barclays corporate bond index excess returns. The hedged return is the return from a long position in corporate bonds and a short position in a riskfree portfolio that has the same cash flow of the corporate bond. The price of riskfree portfolio is determined by its future cash flows discounted using the zero-coupon yield curve from Gurkaynak, Sack and Wright (2007). The Barclays corporate bond index excess return is the difference between the Barclays corporate bond index return and one month Treasury bill rate. The statistical significance of R^2_{OS} is based on the p-value of the out-of-sample MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance level of 1%, 5%, and 10%, respectively.

		Monthly(%)			Quarterly(%)		
		FF	RWC	Δ	FF	RWC	Δ
		In-sample R squares					
Hedged return	AAA	0.05	2.68	2.63	1.53	7.15	5.62
	AA	3.15	9.99	6.83	9.30	18.18	8.88
	A	4.44	12.07	7.63	12.11	19.49	7.37
	BBB	3.92	15.06	11.14	13.06	20.60	7.54
	Junk	2.26	10.46	8.21	5.97	15.70	9.72
	All	2.60	9.44	6.84	8.79	16.86	8.07
		Out-of-sample R squares					
Hedged return	AAA	-0.72	-1.16	-0.44	-1.98	0.50^a	2.48
	AA	1.66^c	4.46^a	2.80	4.54^a	6.51^a	1.98
	A	1.32^c	4.88^a	3.56	4.33^a	7.18^a	2.85
	BBB	-0.05	4.93^c	4.98^a	5.31^a	7.68^a	2.37
	Junk	1.66^b	4.34^a	2.67	3.73^a	4.32^a	0.59
	All	-0.26	4.64^a	4.90	1.40^a	8.38^a	6.97
		In-sample R squares					
Barclays corporate bond index excess return	AAA	1.04	6.75	5.71	3.68	9.54	5.86
	AA	1.88	6.11	4.23	5.08	12.28	7.20
	A	2.83	6.57	3.74	6.40	12.65	6.25
	BAA	6.57	10.26	3.70	15.18	20.43	5.25
	Junk	4.04	15.97	11.93	11.90	21.21	9.31
	All	4.96	9.63	4.67	11.15	18.14	6.99
		Out-of-sample R squares					
Barclays corporate bond index excess return	AAA	-2.22	-0.74	1.48	0.90^c	-1.30	-2.19
	AA	-0.60	0.11^c	0.71	1.49^b	5.04^a	3.55
	A	1.32	2.25^b	0.93	2.11^b	5.31^a	3.19
	BAA	6.65^a	8.37^a	1.72	13.09^a	16.91^a	3.82
	Junk	3.66^a	8.58^a	4.92	5.53^a	12.56^a	7.04
	All	3.98^b	7.02^a	3.04	9.48^a	15.87^a	6.38

Table 12. Out-of-sample forecasts under different economic regimes
This table reports the out-of-sample R-squares of monthly return forecasts using the RWC approach during good, normal and bad growth periods between 1983 and 2012. The statistical significance of R^2_{OS} is based on the p-value of the out-of-sample MSPE-adjusted statistic of Clark and West (2007). ^{a}, ^{b}, and ^{c} denote the significance levels of 1%, 5%, and 10%, respectively.

Maturity	GDP	AAA	AA	A	BBB	Junk	ALL
	Good	4.16^a	3.44^a	4.60^b	4.19^b	6.39^b	3.50^a
All	Normal	6.23^a	13.53^a	13.73^a	16.38^a	15.28^a	12.12^a
	Bad	6.19^a	14.06^b	8.85^a	9.98^a	11.77^a	9.59^a
	Good	5.03^a	5.01^a	9.04^b	6.45^b	3.17^b	4.67^a
Short	Normal	3.77^a	13.40^a	11.31^a	25.43^a	19.71^a	10.03^a
	Bad	5.02^a	17.53^a	11.49^a	9.07^a	7.98^a	8.30^a
	Good	5.97^b	4.06^a	3.84^b	1.75^b	3.69^c	4.07^b
5Yrs<Mat.<7Yrs	Normal	2.90^b	10.82^a	9.32^a	15.68^a	16.91^a	10.02^a
	Bad	6.45^a	11.23^a	10.56^a	6.57^b	3.74^a	7.99^a
	Good	3.60^b	3.44^a	4.81^c	3.95^b	3.22^b	3.36^b
7Yrs<Mat.<10Yrs	Normal	3.14^a	13.79^a	15.14^a	11.99^a	20.07^a	14.17^a
	Bad	2.97^b	9.39^b	5.28^a	9.42^a	6.88^a	5.92^b
	Good	-0.26	4.24^c	0.27^c	0.75^b	2.75^b	2.33^b
Long	Normal	5.98^a	10.96^a	14.25^a	6.75^a	14.24^a	11.88^a
	Bad	1.79	3.01^b	3.04	9.90^c	5.32^b	3.95^b

Table 13. Future macroeconomic conditions and the forecasters
This table reports results of the predictive regression

$$\Delta Y_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1},$$

where ΔY_{t+1} is the change in the recession probability (SRP), industrial production growth (IPG), Treasury bill rate (TBL), default yield spread (DFY), implied volatility index (VIX), expected default frequency (EDF), Chicago Fed National Activity Index (CFNAI), or the Aruoba-Diebold-Scotti (2009) business conditions index (ADSI); X_t is the RWC predictor for a given bond portfolio or the PCA predictor. The forecast horizon is one quarter. The t-statistics are calculated using the Newey-West (1987) adjusted standard errors.

X		β	t-stats	$R^2(\%)$	β	t-stats	$R^2(\%)$
			$Y = SRP$			$Y = IPG$	
	AAA	-0.81	-2.28	3.62	1.18	1.37	0.74
	AA	-0.75	-3.16	7.13	1.25	2.23	2.15
RWC	A	-0.80	-3.69	9.21	1.33	2.63	2.82
	BBB	-0.64	-3.72	9.52	1.10	2.75	3.20
	Junk	-0.52	-3.44	8.63	0.88	2.52	2.78
PCA		-0.64	-0.38	-0.11	-0.48	-0.12	-0.21
			$Y = TBL$			$Y = DFY$	
	AAA	-2.12	-1.08	0.75	-0.56	-1.12	0.79
	AA	-0.97	-0.83	0.24	-0.67	-1.71	2.93
RWC	A	-1.00	-1.02	0.33	-0.70	-1.93	3.78
	BBB	-0.52	-0.64	0.02	-0.62	-2.22	4.78
	Junk	-0.68	-1.07	0.35	-0.50	-1.95	4.34
PCA		-4.77	-0.50	0.01	0.22	0.11	-0.21
			$Y = VIX$			$Y = EDF$	
	AAA	-0.29	-1.63	1.97	-0.26	-2.20	3.06
	AA	-0.23	-2.38	4.23	-0.20	-2.61	3.92
RWC	A	-0.20	-2.43	4.41	-0.21	-2.99	4.87
	BBB	-0.16	-2.49	4.31	-0.16	-2.89	4.43
	Junk	-0.14	-2.66	5.15	-0.14	-3.07	5.01
PCA		-0.43	-0.52	-0.28	-0.21	-0.48	-0.12
			$Y = CFNAI$			$Y = ADSI$	
	AAA	2.08	1.93	1.85	2.01	1.53	1.20
	AA	2.07	2.88	4.35	2.02	2.48	2.98
RWC	A	2.17	3.31	5.51	2.16	2.98	3.94
	BBB	1.84	3.62	6.44	1.79	3.20	4.44
	Junk	1.42	3.15	5.30	1.46	3.04	4.09
PCA		-0.97	-0.19	-0.19	1.06	0.18	-0.20

Figure 1. Bond cumulative returns
This graph plots the cumulative excess returns of rating portfolios and Barclays indicies.

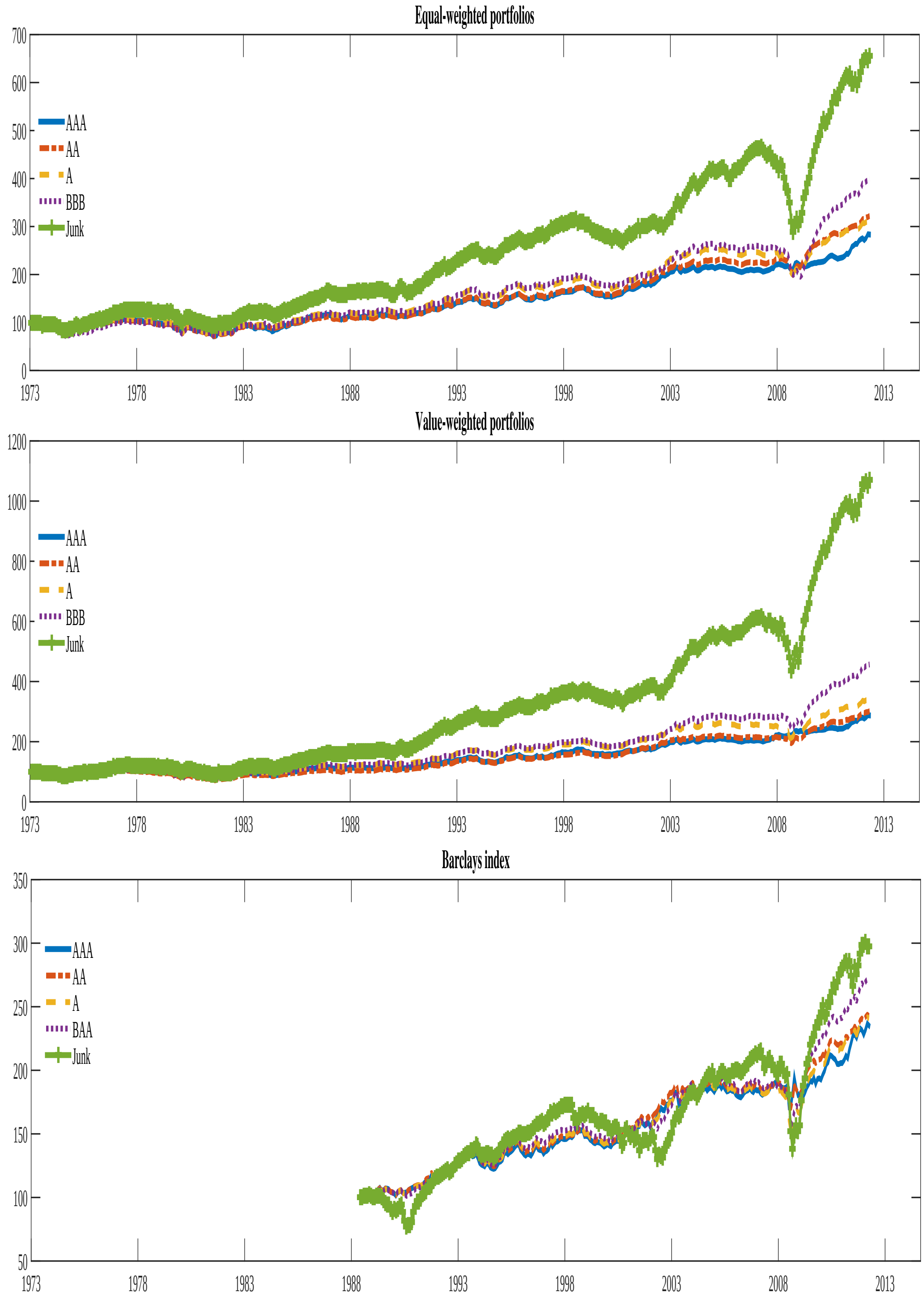

Figure 2. Realized returns and forecasts

This figure plots the realized monthly value-weighted portfolio returns and returns predicted by weighted-average combination (WC) and regressed weighted-average combination (RWC) methods for the AAA long-maturity portfolio.