# Predictability of Corporate Bond Returns: A Comprehensive Study

**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: November 13, 2013

*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 Lubos Pastor and Yongmiao Hong for helpful comments.

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Using a comprehensive data set, we find that corporate bond returns not only remain predictable by traditional predictors–dividend yields, default, term spreads and issuer quality–but also strongly predictable by a new predictor formed by an array of 26 macroeconomic, stock and bond predictors. Results strongly suggest that macroeconomic and stock market variables contain important information for expected corporate bond returns. The predictability of returns is of both statistical and economic significance, and is robust to different ratings and maturities.

*JEL classification*: G12; G14;

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

# 1 Introduction

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. Fama and French (1989) find that dividend yields, default and term spreads can predict corporate bond returns both in and out of sample. Recently, Greenwood and Hanson (2013) have identified issuer quality as an additional predictor for lower rated corporate bond return. The lack of studies on corporate bond predictability is partly due to the unavailability of large systematic corporate bond data until recently. The size of the corporate bond market is about the same as that of stocks, and it is important to understand their time-varying risk premiums. Moreover, besides asset pricing and portfolio allocations, understanding corporate bond predictability aids financial managers in managing firms' exposure to interest rates, which is arguably the largest financial risk to large non-financial firms.

In this paper, we conduct a comprehensive study in an attempt to answer four major questions on the predictability of corporate bond returns. The first is whether or not corporate bond returns are predictable at all. Although Fama and French (1989) found predictability long ago based on 100 corporate bonds, it is unclear whether the same conclusion holds today, after more than 20 years have passed, for an entire universe of corporate bonds. We address this issue by employing a large data set consisting of all publicly traded corporate bonds in the current over-the-counter market and with a sample period spanning from January 1973 to June 2012.

The second question is whether the predictability is of economic value. The papers by Fama and French (1989) and Greenwood and Hanson (2013) are very important, but neither

[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 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 government bonds.

addresses the issue of economic signficance in corporate bond return forecasts. Although traditional predictors are statistically signficant, it is unclear whether the size of predicted returns is of significant economic value. It is therefore important to provide an assessment of return forecastbility of practical value to investors.

The third question is whether other predictors, especially stock market predictors, have value in forecasting corporate bond returns. Economic intuition suggests that corporate bonds can be viewed as a hybrid of stocks and riskless bonds. High-grade bonds with little default risk behave like government bonds, whereas high-yield bonds with high default risk behave more like stocks. As a result, variables that predict stock and government bond returns should in theory contain useful information for predicting returns of corporate bonds with a range of quality from high to low.

The fourth question is how risk premiums vary with business cycles. Fama and French (1989) are the first to link variations in expected corporate bond returns to business conditions. However, their inference is based on in-sample forecasts. It is unclear whether out-of-sample forecasts of the corporate bond premium are also tied to business conditions. While this and the preceding two issues have recently been investigated in studies on stock market predictability (see, for example, Campbell and Thompson, 2008, and Henkel, Martin and Nardari, 2011), none of these issues has been addressed in the corporate bond literature.

Our empirical findings have shed light on these important issues. On the first question, we find that the same three predictors–dividend yields, and default and term spreads–discovered more than 20 years ago by Fama and French (1989), continue to predict corporate bond returns both in and out of sample. The predictability of returns is statistically significant, and is robust to different ratings and maturities. Results suggest that these predictors are at least part of the driving forces behind the time-varying investment opportunity set of corporate bond returns. However, since the predictors do not include common stock and macroeconomic predictors, among others, they only establish a lower bound on the predictability, and thus their economic value is limited, as shown later in our empirical study.

To address the second question, we introduce a method in the recent literature to extract information from a large set of variables to forecast corporate bond returns. This method allows us to obtain a univariate forecaster out of 26 stock, government bond and macroeconomic predictors, otherwise it would be nearly impossible to use all of them in a predictive regression model. The conventional approach to exploit a wealth of predictors is using the factor analysis or the forecast combination method. However, due to high correlations among some of the predictors and the existence of common error components, neither conventional principal component analysis (PCA) nor forecast combination methods can pool the information effectively out of the vast predictors. Fortunately, the partial least squares (PLS) method of Wold (1975), which is developed further by Kelly and Pruitt (2012, 2013), can be used in our context. Unlike the traditional PCA and forecast combination methods, the PLS method is able to purge the common error components of individual predictors and retain the important information content relevant for expected corporate bond returns.

With the PLS approach, we are able to obtain a new forecaster that efficiently incorporates the information from all the 26 predictors. We find that this new forecaster has much higher predictive power than default and term spreads, and issuer quality. For example, it on average delivers an in-sample $R^2$ of 9.04% at the monthly return horizon, in contrast with 3.92% for the Fama-French model (default and term spreads) and 2.29% for the Greenwood-Hanson model that adds issuer quality to the predictive regression. At the same time, PCA performs poorly with an $R^2$ of only 0.25%, suggesting that forecasts by using the PCA method are far from optimal. The predictive power increases with the return horizon. For the PLS method, the $R^2$ increases to 11.45%, whereas it is capped at 8.52% for the Fama-French model and at 6.37% for the Greenwood-Hanson model at the quarterly horizon.

The results for out-of-sample forecasts are also impressive. The new predictor generates out-of-sample $R^2$ values of 7.32% and 9.35% at the monthly and quarterly horizons, respectively. These compare with 3.51% (7.36%) for the Fama-French model and 0.71% (3.25%) for the Greenwood-Hanson model at the monthly (quarterly) horizon. The results show that the stock and bond market variables do have significant incremental predictive power over the traditional predictors.

On the third question, we find that the utility gains from the new predictor are of economic significance. For an investor with a mean-variance utility whose risk aversion is five, the annualized utility gains (certainty equivalent returns) from ignoring the predictability completely to using the predictability are 5.57% (2.03%) for our model with the new predictor at monthly (quarterly) horizon. By contrast, the gains are only 1.64% (1.43%) for the Fama-French model and -0.32% (0.19%) for the Greenwood-Hanson model at the monthly (quarterly) horizons. Thus, our predictive model also generates significantly higher economic values.

On the fourth question, as is the case in the stock market (Henkel, Martin and Nardari, 2011), return predictability tends to be higher in a bad economy than in a good economy. In general, for a given state of the economy, the predictability of corporate bond returns is higher for investment-grade bonds and for shorter-maturity bonds.

Overall, our empirical results strongly suggest that stock and bond market variables contain useful information for expected corporate bond returns. The evidence that some macroeconomic variables have predictive power echoes the finding of Joslin, Priebsch and Singleton (2013) that macroeconomic factors contain important information for bond term structure. Including these variables produces forecast results which are more significant both statistically and economically than the conventional models that use default and term spreads and issuer quality as predictors for corporate bond returns.

The remainder of the paper is organized as follows. Section 2 presents the empirical methodology for testing the return predictability of corporate bonds. Section 3 discusses data and presents empirical results. Finally, Section 4 summarizes important findings and concludes the paper.

# 2 The Methodology

This section outlines the procedure used to extract a univariate predictor from a large set of individual predictors, compares this with other procedures and then discusses the methods to evaluate out-of-sample forecasting performance.

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

$$r_{t+1} = \alpha + \beta z_t + \varepsilon_{t+1}, \tag{1}$$

where $r_{t+1}$ is the return of corporate bonds in excess of the riskless rate, $z_t$ can be the univariate predictor extracted from all individual predictors, or represent only a subset of individual predictors at time $t$ and $\varepsilon_{t+1}$ is an error term. For the Fama-French (1989, FF) model, the vector $z_t$ includes term spreads, default spreads and/or dividend yields, while for the Greenwood-Hanson (2013, GH) model, it includes issuer quality, default and term spreads, Treasury bill rates and, in the case of speculative-grade bonds, past high-yield bond returns.

We now describe the procedure to extract a univariate predictor based on information from a set of observed predictors. The key is to extract the informational component from individual predictors while at the same time removing the common error component. In general, let $x_t = [x_{1t}, \ldots, x_{Nt}]'$ be an $N \times 1$ vector of individual predictors in period $t$ ($t = 1, \ldots, T$) and $r_{t+1}$ be the return on corporate bonds in excess of the riskless rate in period $t + 1$. Following Wold (1975) and Kelly and Pruitt (2012, 2013), we assume that $x_{it}$ has the following factor structure,

$$x_{it} = \lambda_{i0} + \lambda_{i,1} F_t + \lambda_{i,2} E_t + \epsilon_{it}, \tag{2}$$

where $F_t$ is the factor that contains relevant information for the bond return, $E_t$ is the common error components that are irrelevant to the bond return and $\epsilon_{it}$ is the idiosyncratic noise term associated with predictor $i$ only. The novel idea of the PLS procedure is to estimate the latent information factor $F_t$ efficiently while at the same time eliminating the common error component $E_t$ and idiosyncratic noise $\epsilon_{it}$ that are irrelevant to bond returns.

In the bond literature, the latent factor is often estimated by PCA. In this case, it implies using the first principal component (PC) from the cross section of $x_{it}$'s, but this estimator is inefficient. By construction, this principal component is a linear combination of $x_{it}$'s that captures the covariance among the predictors and explains the largest faction of the total variations in $x_{it}$. This procedure unfortunately will contain the common error component that is irrelevant to corporate bond returns. As a consequence, the PC may contain substantial noise which renders it ineffective as a predictor. Put differently, the PC that best explains the variations of the $x_{it}$'s is not necessarily the factor most useful for forecasting bond returns.

In contrast, following Wold (1975) and Kelly and Pruitt (2012, 2013), extracting out the $F_t$ component provides the best predictor. This is done by a two-step procedure. In the first step, we run a time-series regression of $x_{it}$ on corporate bond returns

$$x_{it} = \pi_{i0} + \pi_i r_{t+1} + \varepsilon_{it}, \quad t = 1, \ldots, T, \tag{3}$$

for each predictor $i$. Then, in the second step, we run a cross-sectional regression of $x_{it}$ on the loading $\widehat{\pi}_i$ estimated from the first-step regression,

$$x_{it} = PLS_t \widehat{\pi}_i + \eta_t, \quad i = 1, \ldots, N, \tag{4}$$

for each period $t$. The coefficient in the second-step regression, $PLS_t$, is the extracted predictor that will be used to forecast corporate bond returns. In this estimation procedure, the weight of the individual predictor in the construction of $PLS$ is based on its covariance with the expected return, $r_{t+1}$. The higher the covariance, the greater the weight given to an individual predictor.

Mathematically, the predictor over time as a vector can be expressed as

$$PLS = XX' J_T R (R' J_T X X' J_T R)^{-1} R' J_T R,$$

where $X$ denotes the $T \times N$ matrix of individual predictors, $R$ denotes the $T \times 1$ vector of expected corporate bond returns, $J_T = I_T - \frac{1}{T} l_T l_T'$, with $I_T$ the $T$-dimensional identity matrix and $l_T$ a $T$-vector of ones. The weights for the individual predictors are $X' J_T R$ adjusted by the scalar coefficient $(R' J_T X X' J_T R)^{-1} R' J_T R$. $X' J_T R$ denotes the $N \times 1$ vector of the estimated covariance between individual predictors and expected corporate bond returns.

An important feature of $PLS_t$ is that it is data dependent. The same set of individual predictors will give different $PLS_t$ values for different bond returns to be predicted. This approach lets the data tell us which combination of individual predictors is optimal for predicting the return of a specific class of corporate bonds. For example, it makes great sense to weight stock predictors more heavily for predicting junk bond returns.

In this paper, we also conduct extensive out-of-sample forecasts. The procedure is exactly the same as the above in-sample forecast except that it is done recursively (see, for example, Welch and Goyal, 2008). 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 $t+1 = m$. Similarly, at any future time $t+1$, all available data up to $t+1$ are used for parameter estimation and for forecasting the excess return at $t+2$, and so forth until $T-1$.

Campbell and Thompson (2008) impose weak restrictions that both the coefficient of the predictive regression and risk premium should be positive to be consistent with theory. They show that the sign restriction can minimize the impact of perverse results on out-of-sample forecasts when a regression is estimated over a short sample period. We impose similar sign restrictions in out-of-sample forecasts of corporate bond returns. Specifically, the regression coefficient is set to zero whenever it has a wrong sign and the forecast is set to zero whenever the forecast of the corporate bond premium is negative.

Following Fama and French (1989) and Campbell and Thompson (2008), we evaluate the out-of-sample performance of the model relative to the updated historical average by calculating the following out-of-sample $R^2$ statistic:

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T-k} \left(r_{t+k} - \hat{r}_{t+k}\right)^2}{\sum_{t=1}^{T-k} \left(r_{t+k} - \overline{r}_{t+k}\right)^2}, \tag{5}$$

where $r_{t+k}$ is the realized return at $t+k$, $\hat{r}_{t+k}$ is the out-of-sample forecast from the predictive regression, $\overline{r}_{t+k}$ is the out-of-sample forecast based on the updated historical average, $t$ indicates the time that the forecast is made, $k$ is the number of periods ahead in the forecast and $T$ is the sample size. $R^2_{OS}$ measures the improvement in mean square prediction errors (MSPE) for the predictive regression model over the historical average forecast. The predictive regression forecast outperforms the historical average forecast when $R^2_{OS} > 0$.

We test the statistical significance of $R^2_{OS}$ by the $p$-value of the MSPE-adjusted statistic of Clark and West (2007). This is a one-sided test of the null hypothesis that expected square prediction errors from the historical average and the predictive regression model are equal, against the alternative that the competing predictive model has lower square prediction errors than the historical average forecast. To perform the test, we first compute the following square error difference:

$$e_{t+k} = (r_{t+k} - \overline{r}_{t+k})^2 - [(r_{t+k} - \hat{r}_{t+k})^2 - (\overline{r}_{t+k} - \hat{r}_{t+k})^2] \tag{6}$$

By regressing $e_{t+k}$ on a constant, the $t$-statistic of the constant term then gives a $p$-value for the one-sided (upper tail) test under the standard normal distribution. For the out-of-sample forecast horizon longer than a month, we use the Hodrick (1992) method to correct the impact of overlapping residuals on standard errors.[2]

We assess whether adding explanatory variables significantly improves the predictive power of the model, using the test of Harvey, Leybourne, and Newbold (HLN, 1998). The null hypothesis is that the model $i$ forecast encompasses the model $j$ forecast against the one-sided alternative hypothesis that the former does not encompass the latter. Denote $d_{t+k} = (\hat{u}_{i,t+k} - \hat{u}_{j,t+k})\hat{u}_{i,t+k}$, where $\hat{u}_{i,t+k} = r_{t+k} - \hat{r}_{i,t+k}$, $\hat{u}_{j,t+k} = r_{t+k} - \hat{r}_{j,t+k}$ and $\hat{r}_{j,t+k}$ is the $k$-period ahead return predicted by model $j$. The test statistic is

$$HLN = \frac{T-k-1}{T-k}\hat{V}(\overline{d})^{-1/2}\overline{d} \tag{7}$$

where $\overline{d} = \frac{1}{T-k}\sum_{t=1}^{T-k} d_{t+k}$, $\hat{V}\left(\overline{d}\right) = (T-k)^{-1}\widehat{f}_0$ and $\widehat{f}_0 = (T-k)^{-1}\sum_{t=1}^{T-k}\left(d_{t+k} - \overline{d}\right)^2$ which has a $t_{T-k-1}$ distribution. Again, we adjust standard errors by the Hodrick (1992) method for the effect of overlapping residuals. The HLN statistics are used to test whether a set of forecasting variables contains additional information not already in another set of forecasting variables.

Following Campbell and Thompson (2008) and others, we also 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 predicted returns calculated from the out-of-sample forecast.[3] The measure can also be interpreted as the fee investors being willing to pay to obtain the forecast versus using the historical average. With the historical average forecast, the investor in period $t$ allocates the following proportion of the portfolio to risky securities:

$$w_{0,t} = \left(\frac{1}{\gamma}\right)\left[\frac{\overline{r}_{t+1}}{\widehat{\sigma}^2_{t+1}}\right], \tag{8}$$

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

[3] 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).

where $\widehat{\sigma}^2_{t+1}$ is the rolling-window estimate of the variance of bond excess returns, $\gamma$ is the risk aversion coefficient, and $\overline{r}_{t+1}$ is the historical average return. A 10-year rolling window is used to estimate the variance, which recognizes that more recent information is more important than the distant past information. Over the out-of-sample period, the investor obtains an average utility level of

$$U_0 = \widehat{\mu}_0 - \frac{1}{2}\gamma\widehat{\sigma}^2_0, \tag{9}$$

where $\widehat{\mu}_0$ and $\widehat{\sigma}^2_0$ are the sample mean and variance of returns of the portfolio formed by the excess return forecast based on the historical average.

On the other hand, using a predictive regression model to forecast excess returns, the investor will allocate the following proportion of the portfolio to risky securities:

$$w_{0,t} = \left(\frac{1}{\gamma}\right)\left[\frac{\hat{r}_{t+1}}{\widehat{\sigma}^2_{t+1}}\right], \tag{10}$$

and over the out-of-sample period realizes a utility level of

$$U_1 = \widehat{\mu}_1 - \frac{1}{2}\gamma\widehat{\sigma}^2_1 \tag{11}$$

where $\widehat{\mu}_1$ and $\widehat{\sigma}^2_1$ are the sample mean and variance of returns of the portfolio formed by the forecast of excess returns using the predictive model. The difference between $U_1$ and $U_0$ measures economic significance. A value of 2% or more is usually regarded as economically significant.

## 3 The data and predictive variables

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 characteristics.

The LBFI database consists of monthly data for corporate bond issues from January 1973 to March 1998. The database includes month-end prices, accrued interest, rating, issue date, maturity and other bond characteristics. Datastream reports the daily corporate bond price, which is an average price across all market makers for that bond. We select only US dollar-denominated bonds with regular coupons and collect the data up to June 2012. The TRACE and NAIC databases contain transaction data for corporate bonds. NAIC includes data on corporate bonds traded by life, property and casualty insurance companies, and health maintenance organizations (HMOs). TRACE data begin in July 2002 and NAIC data start from January 1994. TRACE initially covers only a small portion of corporate bond trades and we use the data from NAIC to augment the sample size. We use the procedure suggested by Bessembinder, Kahle, Maxwell, and Xu (2009) to filter out cancelled, corrected and commission trades. We compute daily prices as the trade size-weighted average of intraday prices over the day. The FISD database includes issue- and issuer-specific information for bonds maturing in 1990 or later. The data items include coupon rate, issue date, maturity date, issue amount, rating, provisions and other bond characteristics. We collect bond characteristics information from this database.

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 $t$.[4] We drop the Datastream data if returns are available from other sources. When both LBFI data and transaction-based data are available, we choose transaction-based data. The combined corporate bond return data run from January 1973 to June 2012. We exclude bonds with maturity less than two years and longer than 30 years and select only straight bonds to avoid confounding effects of embedded options. We also exclude the bonds with a rating below B.

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

[4] 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.

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 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.

6. Book-to-market ratio, B/M: Ratio of book value to market value for 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).[5]

In addition, we use a number of variables considered to be important for predicting bond returns from the bond literature (see Collin-Dufresne, Goldstein and Martin, 2001; Cochrane and Piazzesi, 2005). 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, 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 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.[6] 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 with in-sample $R^2$ as high as 44%. This CP factor is constructed from the parameters

[5]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.

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

of the following regression:

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1 y_t^{(1)} + \gamma_2 f_t^{(2)} + \cdots + \gamma_5 f_t^{(5)} + \bar{\varepsilon}_{t+1} \tag{13}$$

or in vector form,

$$\overline{rx}_{t+1} = \boldsymbol{\gamma}^T \mathbf{f}_t + \bar{\varepsilon}_{t+1}$$

where $rx_{t+1}^{(n)}$ is the log holding period return from buying an $n$-year Treasury bond at time $t$ and selling it as an $n$-1 year Treasury bond at time $t$+1 minus the one year interest rate at time $t$, $y_t^1$, and $f_t^{(n)}$ is a forward rate at time $t$ for loans between time $t$+$n$-1 and $t$+$n$. The $\gamma$ coefficients from the regression can be used to construct the CP factor $\boldsymbol{\gamma}^T \mathbf{f}_t$ for forecasting bond returns. The original CP regression uses the forward rates up to the fifth year, which we refer to as the CP five-year factor. 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 $\hat{\gamma}$, and construct the linear combination $\boldsymbol{\gamma}^T \mathbf{f}_t$ as the CP factor.[7]

Aside from the CP five-year factor, we construct an alternative CP factor with maturity $n = 10$ to capture the longer-term interest rate expectations. As expectations of distant future interest rates affect prices of long-term bonds with varying maturities, distant forward rates may help forecast returns of long-term bonds. The CP factor with $n = 10$ can be easily obtained by extending the maturity in (13) to 10 years:

$$\frac{1}{9}\sum_{n=2}^{10} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1 y_t^{(1)} + \gamma_2 f_t^{(2)} + \cdots + \gamma_5 f_t^{(5)} + \cdots + \gamma_9 f_t^{(9)} + \bar{\varepsilon}_{t+1} \tag{14}$$

The above forward rate factor is referred to as the CP 10-year factor.

To estimate (14), we collect yield data from the Federal Reserve Bank (FRB) for Treasury securities with constant maturities of six-month, one-, two-, three-, five-, seven-, and 10-year to estimate spot and forward rates. The FRB six-month constant yield-to-maturity data start only from 1982, and we use the six-month Treasury bill rate instead for the period before 1982. Moreover, as the data of two-year constant yield-to-maturity are available only from 1976, we use the interpolation of one-year and three-year yields for the period

[7] The estimates of $\gamma$ are $\hat{\gamma}_0 = -1.52$ , $\hat{\gamma}_1 = -1.59$ , $\hat{\gamma}_2 = -0.09$ , $\hat{\gamma}_3 = 3.20$ , $\hat{\gamma}_4 = 0.81$ and $\hat{\gamma}_5 = -2.08$. The adjusted R-square is 25%.

from 1973 to 1976. We employ a standard cubic spline algorithm to interpolate these par yields at semi-annual intervals and bootstrap them to provide a discount rate curve (see also Longstaff, Mithal and Neis, 2005).[8]

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

$$IQ_t = \frac{\sum_{j=0}^{j=11} Junk_{t-j}}{\sum_{j=0}^{j=11} Invest_{t-j} + \sum_{j=0}^{j=11} Junk_{t-j}} \tag{15}$$

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 1994–2008 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 to be 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 unclear whether this predictor can forecast corporate bond returns. We obtain the outstanding values of annual long- and short-term debts from the Federal Reserve Board 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. We also add a negative sign to the debt maturity factor (ratio) to make the predictive relationship become positive.

**The liquidity factor**

[8]The standard cubic spline is $z = a_0 + a_1x + a_2x^2 + a_3x^3$ .

Næs, Skjeltorp, and Ødegaard (2011) find a strong predictive relation between stock market liquidity and the business cycle. Since asset risk premia are related to business conditions, aggregate liquidity may predict corporate bond returns. We investigate this possibility by using various liquidity measures to capture different dimensions of market liquidity described below.

***Changes in money market mutual fund flows, MMMF***

We obtain monthly changes in total money market mutual fund assets (MMMF, in billions) from the Federal Reserve Bank. Money market mutual funds represent a hedge against a flight-to-quality or liquidity. A sudden increase in the amount of funds flowing into money market mutual funds is typically associated with lack of liquidity in other markets with risky assets, such as corporate bonds.

***On-/off-the-run spread***

The on-/off-the-run spread (*Onoff*) is the difference between the yield of the current on-the-run 5-year Treasury bond and the average yield of generic off-the-run Treasury bonds with the same maturity. The on-the-run yield is the constant maturity 5-year Treasury rate calculated by the Federal Reserve from the benchmark on-the-run issues. The off-the-run yield is the 5-year generic Treasury rate reported in the Bloomberg system, which is based on the yields of the non-benchmark Treasury bonds. 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).

***Pastor-Stambaugh and Amihud stock market liquidity measures***

Two widely used market 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. In addition, we construct the Amihud stock (AmS) measures using the methods suggested by Acharya and Pedersen (2005) and Lin, Wang and Wu (2011). For ease of comparison with other illiquidity measures, we add a negative sign to the PS liquidity measures to make them consistent with the on-/off-the-run spread and Amihud measures;

both are proxies for illiquidity. The converted PS indices measure market illiquidity.

***The effective cost index, EC***

The last marketwide liquidity measure considered in this study is the effective cost index constructed by Hasbrouck (2009) for the stock market. This index measures liquidity from the dimension of trading cost. The effective cost index is downloaded from Hasbrouck's website, and this data end in 2005.

Using the above mentioned predictors, we consider the following predictive regressions:

1. The predictive regression using the above individual predictors;
2. The predictive regression using the extracted predictor (PLS) by applying the partial least squares method to all 26 predictors;
3. The predictive regression using the first principal component of all predictors;
4. The multiple predictive regression using term and default spreads (FF),[9] and then adding Treasury bill rates, lagged high-yield bond returns and the issuer quality factor (GH).

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 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. Using different market variables in the regression allows us to see the role of each variable in the predictability of corporate bond returns.

[Insert Table 1 here]

[9] We also try the other model used in Fama and French (1989), that is, using the term spread and D/P ratio as the predictors. The results are close to those of using the term spread and default spread. The results are available upon request.

Table 2 summarizes the distribution of corporate bond data. As shown, 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 a little less than 10% of the sample, with 71,557 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, TRACE contributes the most to the data sample (256,060 observations), followed by LBFI (256,015 observations), Datastream (143,990 observations) and NAIC (110,036 observations).

[Insert Table 2 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.

Table 3 reports summary statistics for rating portfolios 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.

[Insert Table 3 here]

To examine the dynamics of return of different portfolios, we transform the return series into the index series by

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

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

Figure 1 plots the time series of the indices for 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 of 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 are quite smooth for AAA bonds. This pattern is attributable to flights-to-quality during the crisis period. In empirical tests, for brevity we only report results of the value-weighted portfolios.

[Insert Figure 1 here]

Figure 2 plots the time series of the extracted predictor, PLS, by applying the partial least squares method to 26 individual predictors. The monthly excess return of corporate bond is used in the first-step regression. The upper, middle and bottom panels plot the PLS variable for rating portfolios, short-maturity portfolios and long-maturity portfolios, respectively. As shown, there are strong comovements among the PLS series of different ratings, while that of junk bonds is more volatile.

[Insert Figure 2 here]

# 4 Empirical Results

## 4.1 In-sample forecasts

Table 4 reports the in-sample $R^2$ of the predictive regressions for each single predictor listed in Table 1. For brevity, we report the results only for rating portfolios to give an overall picture. The left panel reports results of monthly forecasts, and the right panel reports results of quarterly forecasts. Results show that a number of variables associated with the stock and bond markets can predict corporate bond returns in sample with relatively high $R^2$. Besides default spreads (DFY), these include variables such as term spread (TMS), liquidity indices, for example, on-/off-the-run spreads (Onoff), changes in money market mutual fund flows ($\Delta$MMMF), long-term government bond returns (LTR), inflation rates

(INFL), the Cochrane-Piazzesi forward rate factor (CP5 and CP10), leverage ratio (LEV2), earning-price ratio (E/P), dividend-payout ratio (D/E) and stock return variance (SVAR). These variables have $R^2$ higher than or comparable to default spreads. Consistent with Joslin, Priebsch and Singleton (2013), we find that macroeconomic factors contain important information to forecast corporate bond returns.

[Insert Table 4 here]

Table 5 reports the estimated covariance of individual predictors with expected returns of rating portfolios. These covariance estimates are used to obtain the weights of individual predictors for constructing the univariate forecaster PLS. The higher the absolute value of the covariance, the greater the weight assigned for that predictor.

Results show that the traditional predictors in the literature, such as term spreads (TMS), default spreads (DFY), and Treasury bill rates (TBL), are indeed important. More importantly, other variables of stock and Treasury markets have significant contribution to the construction of PLS. These include earning yields (E/P), dividend payout (D/E), leverage ratios (LEV1 and LEV2), long-term bond returns (LTR), inflation rates (INFL), CP factors (CP5 and CP10), percentage changes in the money market mutual fund flows ($\Delta$MMMF) and on-/off-the-run spread (Onoff). For the monthly horizon, the on-/off-the run spread has the largest covariance, giving the highest weight in the construction of PLS. For the quarterly horizon, CP10 has the largest weight for AAA bonds. These findings suggest that it is important to consider other variables besides those used in the literature to forecast the corporate bond returns.

An interesting finding in Table 5 is that returns of low-grade bonds have higher covariance with the stock market variables. For example, the covariances of returns with earning yields (E/P), dividend payout (D/E), S&P 500 index returns (S&P 500), the aggregate leverage ratio (LEV2), effective trading cost (EC) and issuer quality (IQ) are all highest for junk bonds, suggesting that they are more correlated with high-yield bond returns. Results support the traditional view that speculative-grade bonds behave more like stocks.

[Insert Table 5 here]

Table 6 reports the in-sample $R^2$ of predictive regressions using the extracted predictor (PLS), the first principal component (PCA), term and default spreads (FF), and Treasury bill rates, term spreads, default spreads, lagged high-yield bond returns and the issuer quality ratio (GH). We report results for rating portfolios as well as the maturity portfolios in each rating. FF has a good predictive performance in sample, giving an average in-sample $R^2$ of 3.92% for monthly forecast and 8.52% for the quarterly forecast.[10] Although not reported in the table for brevity, the corresponding $R^2$'s are 7.05% and 13.25% over 1973–1987, which covers part of the FF sample period, and 1.90% and 4.80% in the post-FF period 1988–2012, again confirming that default and term spreads have consistent predictive power over time. The result suggests that FF predictors capture some of the fundamental driving forces in the corporate bond risk premium.

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

The PLS forecaster, which removes common noises among a set of predictors, provides a better prediction of bond returns than FF and GH by delivering much higher in-sample $R^2$. For the monthly forecast, the $R^2$ using the PLS forecaster is 9.04% on average. For the quarterly forecast, it goes up to 11.45%. By contrast, the principal component forecaster PCA has very poor in-sample performance. The last column in each panel reports the difference of in-sample $R^2$ between the prediction using PLS and that using the Fama-French default and term spreads. Most of them are positive, with the maximum value equal to 7.96% for the monthly forecast and 6.01% for the quarterly forecast. Similar results (not reported) are obtained even if we add the dividend yield to the Fama-French model. The finding of better performance for PLS is robust across ratings and maturities. Results show that the PLS forecaster has much higher predictive power than default and term spreads.

[Insert Table 6 here]

[10]We use the results of a portfolio constructed by all rating and maturity data as the average measure.

### 4.2 Out-of-sample forecasts

Table 7 reports the out-of-sample $R^2$ of the predictive regression model. When performing the out-of-sample forecast at time $t$, we only use the available information up to time $t$ to extract the PLS forecaster and the first principal component. Similar to in-sample results in Table 5, FF and GH predictors have out-of-sample forecast ability. The out-of-sample $R^2$ using the FF variables is 3.51% for the monthly forecast, and 7.36% for the quarterly forecast. The results for the GH variables are much weaker but still significant. The worst performer is PCA. Most of the out-of-sample $R^2$s of PCA are negative, suggesting that the principal component is a suboptimal forecaster.

The PLS forecaster has the best out-of-sample predictive performance among all. The out-of-sample $R^2$s are significantly positive. For the monthly forecast, it can be as high as 11.79% (AA short-maturity portfolio). The average out-of-sample $R^2$ of the monthly forecast using PLS is 7.32%. For the quarterly forecast, it could reach 15.51% (AA short-maturity portfolio) and the average is 9.35%. Both are much higher than FF and GH. These figures are also higher than those of stock market predictability. 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. Results suggest that the corporate bond market is more predictable than the stock market.

The last column of the left and right panel of Table 7 reports the difference in $R^2$ between the models using PLS and FF forecasters. Most of these figures are positive, suggesting that the PLS forecaster has a higher predictive power than default and term spreads of FF. The improvement of monthly forecasts by PLS is more significant than that of quarterly forecasts. Similar to in-sample results, the improvement is quite robust across ratings and maturities.

[Insert Table 7 here]

Figure 3 plots ex post monthly returns and predicted returns for rating portfolios by historical mean (HM) and forecasting with PLS. Results show that return forecasts by PLS exhibit a shape similar to ex post returns, which reflects the better performance of forecasting by the PLS method. By contrast, the predicted returns by historical mean are quite flat and show a pattern very different from ex post returns. Figure 4 plots ex post monthly returns and predicted returns for maturity portfolios in each rating category. Again, the PLS method predicts the return out-of-sample much better than does the historical average.

[Insert Figures 3 and 4 here]

### 4.3 Economic significance

Table 8 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.[11] The left panel reports results of monthly forecasts, while the right panel reports results of quarterly forecasts.

[Insert Table 8 here]

Results show that the utility gains by FF and GH are not consistent across rating portfolios and maturity portfolios. For the monthly forecast, most of them are negative, suggesting that they are economically insignificant. For the quarterly forecast, the results of FF are better but there are still some negative CER values. Utility gains of forecasts by the GH variables are negative. These results show a dramatic difference between the statistical significance (Table 7) and the economic significance (Table 8) for the FF and GH models. Finally, the PCA continues to perform the worst.

In contrast, the PLS forecast is not only statistically significant but economically significant. All utility gains using the PLS forecaster are positive. For the monthly forecast, the gain of economic value could reach 7.66% (junk short-maturity portfolio), and on average it is 5.57%. For the quarterly forecast, the gain is 2.03% on average. These results are also stronger than those in the stock market reported in Rapach, Strauss and Zhou (2010).[12]

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

[12] In Table 1 of Rapach, Strauss and Zhou (2010), they report an annualized utility gain of quarterly forecast around 0.50% during 1976–2005.

The last column of both panels reports the difference in utility gains between the models using PLS and FF predictors. All figures are positive for the monthly forecast and negative in only one case for the quarterly forecast. The improvement in economic values is more significant for the monthly forecast, and results are again robust across ratings and maturities.

## 4.4 Forecast encompassing tests

To further evaluate the performance of different models, we conduct forecast encompassing tests. If the PLS model has successfully extracted all relevant information in the predictors, then adding the variables in the Fama-French and Greenwood-Hanson models should not improve the forecasting power of the PLS model. The encompassing test does exactly this job of discriminating the performance of competing models.

We calculate the MHLN statistics of Harvey, Leybourne, and Newbold (1998) to test whether the forecast by the model with the PLS forecaster encompasses the forecasts by the FF and GH models or vice versa. Table 9 reports results of encompassing tests based on monthly return forecasts. 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 model with the PLS forecaster encompasses the FF, GH and PCA models. On the other hand, the FF, GH and PCA models all fail to encompass the PLS model. Results strongly suggest that the model with the PLS forecaster contains all the information in the FF, GH and PCA models. This finding confirms the superiority of the PLS model and suggests that the PLS forecaster provides the optimal forecasting for corporate bond returns.

## 4.5 Predictability and economic growth

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 investors incentives to invest. Heightened risk aversion when economic conditions are poor demands a higher risk premium, thereby generating risk premium predictability. Rapach, Strauss and Zhou

(2010) find that the predictability of return varies with business conditions. Particularly, out-of-sample gains for a premium forecast linked to business conditions tend to be more predictable when business conditions are poor.

In light of the literature, we examine the predictability of corporate bond returns over periods with different rates of economic growth. To accomplish this, we sort the sample period based on the real GDP growth rate and define the regimes based on the sorted value of real GDP. To ensure that we have enough observations in each regime, we divide the sample into good, normal and bad growth periods using the top, middle and bottom third sorted real growth rates and report the $R^2$s of the out-of-sample forecasts in each regime.

Table 9 reports the results of forecast 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. These results are consistent with the finding of Rapach, Strauss and Zhou (2010) for the stock market, and suggest that the predictability of corporate bond returns is also higher during the low-growth period. The results of maturity portfolios show a similar pattern in that returns are more predictable during the low-growth period. An interesting finding is that the discrepancy in the predictability between bad and good economies tends to widen for long-maturity lower-quality bonds.

[Insert Table 9 here]

## 4.6 Predicted return curve analysis

The value of a financial asset is derived from the discounted future expected cash flows in which the discount rate varies over time. Ang and Liu (2004) study the predicted return curve, which is used as the discount rate curve for cash flows in different periods. Using a similar approach, we investigate the predicted return curve of corporate bonds over different return horizons.

Figure 5 plots the mean predicted returns by PLS for horizons of one month to four years. As expected, the predicted return curve of speculative-grade bonds is much higher than that of investment-grade bonds, confirming that investors use higher rates to discount the cash flows of speculative-grade bonds. The predicted return curves are slightly downward, suggesting that investors use a smaller discount rate for longer-term cash flows of bonds.

[Insert Figure 5 here]

Figure 6 plots the mean expected return by PLS at the peak (July 1990, March 2001 and December 2007) and trough (March 1991, November 2001 and June 2009) of the business cycle for different horizons: monthly, quarterly and one to four years. The business cycle is defined by the NBER's Business Cycle Dating Committee. The predicted return curve is higher at the trough than at the peak, indicating that higher discount rates are used to discount future cash flow when economic conditions are poor. At the peak of the business cycle, the predicted return curve is upward sloping for lower-grade bonds, which implies the investors use higher discount rates for longer-term cash flow. This finding is consistent with the view that when the economy is booming, short-term risk is lower than long-term risk. On the other hand, the predicted return curves are downward sloping at the trough. When the economy is in recession, investors use higher discount rates for short-term cash flow and use lower discount rates for long-term cash flow, since the prospect is expected to improve in the long term.

[Insert Figure 6 here]

# 5 Conclusions

In this paper, we provide a comprehensive study on the predictability of corporate bond returns. Using the partial least squares method, we construct a univariate forecaster from individual predictors, including stock, Treasury and corporate bond market variables. This forecaster is particularly useful for predicting corporate bond returns because the number of likely predictors is large and correlations are high among many of them. We find that the PLS predictor substantially outperforms the Fama-French (1989) model and the Greenwood-Hanson (2011) model in terms of both statistical and economic significance. Corporate bond returns tend to be more predictable for investment-grade bonds and short-maturity bonds.

Moreover, our 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 conventional view that high risk aversion during an economic recession requires a high compensation for risk bearing. Predicted returns are higher at the NBER trough than at the peak, suggesting that higher discount rates are used to discount future cash flow when economic conditions are unfavorable.

Overall, there is strong evidence that stock and bond market variables contain useful information for predicting corporate bond returns. We find that returns of lower-quality bonds are more closely related to stock market variables. This finding confirms the traditional view that high-yield bonds behave more like stocks. Finally, the evidence that macroeconomic variables such as inflation rates, interest rates, stock market returns and liquidity factors have predictive power is consistent with the findings of recent empirical and theoretical studies that macroeconomic factors contain important information for the term structure of defaultable bonds.

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Table 1. Summary statistics of predictors

This table reports the summary statistics for the predictors including 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), and debt maturity index (DM). $\rho$ (1) and $\rho$ (12) are the autoregressive coefficients at lag 1 and 12 of monthly intervals.

| | Predictor | Obs. | Mean | Std. | $\rho$ (1) | $\rho$ (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 | 7.4 | 0.99 | 0.96 |

Table 2. Sample distribution
This table reports the sample distribution of the corporate bond data sample by rating and maturity, and the source. We collect the data 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). We merge data from all sources. We drop the Datastream data if returns are available from other sources. When both LBFI data and transaction-based data are available, we choose transaction-based data. We exclude bonds with maturity less than two years and longer than 30 years and select only straight bonds to avoid confunding effects of embedded options. The combined corporate bond return data are from January 1973 to June 2012.

| Maturity | AAA | AA | A | BBB | BB | B | All |
|---|---|---|---|---|---|---|---|
| Distribution by maturity | | | | | | | |
| 3 | 11,471 | 26,152 | 46,956 | 18,683 | 7,034 | 2,937 | 113,233 |
| 4 | 8,480 | 21,357 | 39,053 | 17,398 | 5,167 | 2,575 | 94,030 |
| 5 | 8,454 | 20,010 | 36,261 | 17,396 | 4,951 | 2,070 | 89,142 |
| 6 | 5,109 | 12,384 | 24,539 | 13,510 | 3,991 | 2,362 | 61,895 |
| 7 | 5,339 | 11,360 | 24,128 | 14,235 | 4,077 | 2,829 | 61,968 |
| 8 | 4,876 | 9,000 | 20,012 | 11,799 | 3,109 | 1,988 | 50,784 |
| 9 | 4,514 | 8,789 | 20,971 | 13,527 | 3,164 | 1,534 | 52,499 |
| 10 | 4,161 | 8,235 | 20,843 | 15,114 | 3,255 | 1,410 | 53,018 |
| >10 | 11,818 | 25,981 | 70,031 | 62,598 | 12,632 | 6,472 | 189,532 |
| All | 64,222 | 143,268 | 302,794 | 184,260 | 47,380 | 24,177 | 76,6101 |
| Distribution by data source | | | | | | | |
| Datastream | 8,326 | 25,613 | 41,863 | 50,450 | 10,695 | 7,043 | 143,990 |
| LBFI | 15,539 | 42,180 | 115,257 | 65,312 | 12,631 | 5,096 | 256,015 |
| NAIC | 25,851 | 14,699 | 39,085 | 22,475 | 5,957 | 1,969 | 110,036 |
| TRACE | 14,506 | 60,776 | 106,589 | 46,023 | 18,097 | 10,069 | 256,060 |
| All | 64,222 | 143,268 | 302,794 | 184,260 | 47,380 | 24,177 | 766,101 |

Table 3. Summary statistics of bond portfolios

This table reports summary statistics of rating portfolio, and short- and long-maturity portfolios in each rating category. In each month, we sort all bonds independently into five rating portfolios and four maturity portfolios. The cut-off values for maturity portfolios are 5 years, 7 years, and 10 years. In all, 20 maturity portfolios are constructed at the intersection of 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 | 0.49 | 2.28 | 0.49 | 0.55 | 2.37 | 0.55 |
| Junk | Short | 0.25 | 2.07 | 0.35 | 0.34 | 2.00 | 0.37 |
| | Long | 0.76 | 2.95 | 0.41 | 0.89 | 3.42 | 0.40 |
| | All | 0.32 | 1.82 | 0.36 | 0.30 | 1.64 | 0.31 |
| All | Short | 0.27 | 1.31 | 0.36 | 0.24 | 1.15 | 0.30 |
| | Long | 0.44 | 2.51 | 0.34 | 0.42 | 2.35 | 0.29 |

Table 4. In-sample R-squares of univariate predictive regressions
This table reports the in-sample R-squares of univariate predictive regressions for rating portfolios. The predictors include 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 ($\Delta$MMMF), on-/off-the-run spread (Onoff), default yield spread (DFY), default return spread (DFR), issuance quality index (IQ), and debt maturity index (DM).

| | Monthly (%) | | | | | | Quarterly (%) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Predictor | AAA | AA | A | BBB | Junk | ALL | AAA | AA | A | BBB | Junk | ALL |
| D/P | 0.10 | 0.19 | 0.00 | 0.05 | 0.01 | 0.08 | 0.33 | 0.42 | 0.00 | 0.07 | 0.27 | 0.23 |
| D/Y | 0.21 | 0.26 | 0.00 | 0.02 | 0.04 | 0.13 | 0.55 | 0.61 | 0.01 | 0.09 | 0.26 | 0.37 |
| E/P | 0.23 | 1.80 | 1.23 | 1.83 | 1.59 | 1.34 | 0.48 | 3.67 | 2.36 | 3.51 | 2.00 | 2.40 |
| D/E | 0.09 | 1.80 | 2.25 | 2.66 | 3.67 | 2.09 | 0.08 | 3.64 | 4.66 | 5.46 | 7.45 | 4.26 |
| SVAR | 1.36 | 2.16 | 1.94 | 1.05 | 0.13 | 1.30 | 2.19 | 5.77 | 4.19 | 3.58 | 2.49 | 2.86 |
| B/M | 0.24 | 0.61 | 0.18 | 0.39 | 0.20 | 0.36 | 0.59 | 1.26 | 0.29 | 0.71 | 0.06 | 0.80 |
| NTIS | 1.12 | 0.65 | 0.52 | 0.21 | 0.01 | 0.79 | 2.08 | 1.26 | 0.59 | 0.39 | 0.04 | 1.37 |
| S&P 500 | 1.74 | 0.45 | 0.00 | 0.86 | 1.37 | 0.63 | 2.77 | 1.38 | 0.52 | 0.02 | 0.00 | 1.54 |
| LEV1 | 0.28 | 0.94 | 1.04 | 0.67 | 0.40 | 0.39 | 0.20 | 1.67 | 2.15 | 1.69 | 3.11 | 0.52 |
| LEV2 | 1.85 | 3.21 | 3.01 | 3.90 | 3.13 | 2.63 | 3.06 | 5.92 | 5.09 | 8.15 | 6.80 | 4.90 |
| EC | 0.49 | 0.85 | 0.80 | 0.45 | 1.05 | 0.59 | 0.35 | 0.87 | 0.76 | 0.72 | 1.27 | 0.58 |
| PSS | 0.01 | 0.39 | 0.29 | 0.84 | 0.44 | 0.22 | 0.40 | 0.14 | 0.09 | 0.03 | 0.04 | 0.17 |
| AmS | 0.13 | 0.25 | 0.34 | 0.00 | 0.03 | 0.11 | 1.14 | 0.59 | 0.43 | 0.07 | 0.00 | 0.71 |
| TBL | 0.76 | 1.72 | 1.16 | 2.47 | 1.83 | 1.37 | 0.99 | 2.63 | 1.51 | 3.98 | 2.64 | 2.05 |
| LTY | 0.09 | 0.30 | 0.05 | 0.37 | 0.25 | 0.16 | 0.00 | 0.15 | 0.01 | 0.24 | 0.10 | 0.02 |
| LTR | 5.29 | 4.53 | 4.47 | 5.95 | 4.40 | 5.76 | 0.65 | 0.74 | 0.52 | 1.04 | 1.69 | 1.11 |
| TMS | 1.95 | 3.67 | 3.82 | 5.61 | 4.29 | 3.41 | 4.83 | 8.15 | 7.94 | 12.05 | 8.74 | 7.99 |
| INFL | 0.76 | 2.30 | 1.52 | 2.27 | 3.56 | 1.98 | 0.54 | 2.68 | 1.87 | 2.63 | 3.67 | 1.98 |
| CP5 | 1.17 | 2.02 | 2.37 | 2.65 | 2.29 | 2.00 | 3.56 | 5.25 | 5.52 | 6.06 | 5.07 | 5.73 |
| CP10 | 2.32 | 3.30 | 2.92 | 2.93 | 3.28 | 3.19 | 6.25 | 6.98 | 6.36 | 6.18 | 5.92 | 7.96 |
| $\Delta$MMMF | 1.24 | 2.10 | 2.55 | 3.06 | 2.85 | 2.14 | 1.73 | 3.28 | 3.96 | 4.92 | 2.43 | 3.26 |
| Onoff | 5.60 | 5.95 | 5.85 | 6.11 | 4.41 | 6.52 | 1.61 | 2.46 | 2.09 | 2.97 | 3.23 | 2.77 |
| DFY | 0.23 | 1.23 | 2.03 | 2.38 | 1.47 | 0.85 | 0.18 | 2.08 | 3.52 | 4.10 | 3.35 | 1.11 |
| DFR | 0.91 | 0.03 | 0.01 | 0.59 | 0.62 | 0.29 | 0.38 | 0.04 | 0.00 | 0.21 | 0.44 | 0.13 |
| IQ | 0.00 | 0.14 | 0.32 | 0.16 | 0.30 | 0.02 | 0.01 | 0.29 | 0.68 | 0.33 | 0.88 | 0.03 |
| DM | 0.12 | 0.34 | 0.21 | 0.87 | 0.36 | 0.22 | 0.14 | 0.47 | 0.21 | 1.39 | 0.46 | 0.29 |

Table 5. Covariance of individual predictors with expected corporate bond returns

This table reports estimates of covariance of normalized individual predictors with expected excess returns of rating portfolios, which are used in calculating the weight of each predictor in constructing the extracted univariate forecaster PLS. 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 ($\Delta$MMMF), on-/off-the-run spread (Onoff), default yield spread (DFY), default return spread (DFR), issuance quality index (IQ), and debt maturity index (DM).

| | Monthly | | | | | | Quarterly | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Predictor | AAA | AA | A | BBB | Junk | ALL | AAA | AA | A | BBB | Junk | ALL |
| D/P | -0.05 | -0.07 | -0.01 | -0.04 | 0.02 | -0.04 | -0.06 | -0.07 | 0.00 | -0.03 | 0.08 | -0.05 |
| D/Y | -0.07 | -0.08 | -0.01 | -0.02 | 0.05 | -0.06 | -0.08 | -0.08 | -0.01 | -0.04 | 0.08 | -0.06 |
| E/P | -0.08 | -0.20 | -0.18 | -0.24 | -0.27 | -0.11 | -0.07 | -0.20 | -0.18 | -0.23 | -0.21 | -0.11 |
| D/E | 0.05 | 0.20 | 0.24 | 0.28 | 0.40 | 0.11 | 0.03 | 0.19 | 0.25 | 0.28 | 0.40 | 0.10 |
| SVAR | 0.11 | 0.13 | 0.13 | 0.11 | 0.04 | 0.10 | 0.09 | 0.14 | 0.14 | 0.14 | 0.14 | 0.10 |
| B/M | -0.08 | -0.12 | -0.07 | -0.11 | -0.09 | -0.09 | -0.08 | -0.12 | -0.06 | -0.10 | -0.04 | -0.09 |
| NTIS | -0.17 | -0.12 | -0.12 | -0.08 | -0.02 | -0.13 | -0.15 | -0.12 | -0.09 | -0.08 | -0.03 | -0.12 |
| S&P 500 | -0.20 | -0.10 | 0.00 | 0.16 | 0.24 | -0.11 | -0.17 | -0.12 | -0.08 | -0.01 | 0.01 | -0.12 |
| LEV1 | 0.08 | 0.14 | 0.16 | 0.14 | 0.13 | 0.09 | 0.05 | 0.13 | 0.17 | 0.16 | 0.26 | 0.07 |
| LEV2 | 0.22 | 0.27 | 0.28 | 0.34 | 0.37 | 0.24 | 0.18 | 0.25 | 0.26 | 0.35 | 0.39 | 0.22 |
| EC | 0.12 | 0.14 | 0.14 | 0.11 | 0.20 | 0.12 | 0.06 | 0.09 | 0.10 | 0.10 | 0.16 | 0.08 |
| PSS | -0.02 | -0.09 | -0.08 | -0.15 | -0.13 | -0.07 | 0.06 | 0.04 | 0.03 | -0.02 | -0.03 | 0.04 |
| AmS | 0.01 | 0.02 | 0.02 | 0.00 | -0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.01 | 0.00 | 0.02 |
| TBL | -0.14 | -0.20 | -0.18 | -0.28 | -0.29 | -0.18 | -0.11 | -0.17 | -0.14 | -0.25 | -0.25 | -0.14 |
| LTY | -0.05 | -0.08 | -0.04 | -0.11 | -0.11 | -0.06 | 0.00 | -0.04 | 0.01 | -0.06 | -0.05 | -0.02 |
| LTR | 0.35 | 0.30 | 0.33 | 0.41 | 0.42 | 0.34 | 0.08 | 0.08 | 0.08 | 0.12 | 0.19 | 0.10 |
| TMS | 0.22 | 0.29 | 0.32 | 0.42 | 0.44 | 0.27 | 0.23 | 0.29 | 0.33 | 0.42 | 0.44 | 0.28 |
| INFL | -0.13 | -0.21 | -0.19 | -0.25 | -0.37 | -0.20 | -0.07 | -0.16 | -0.15 | -0.19 | -0.27 | -0.13 |
| CP5 | 0.17 | 0.21 | 0.24 | 0.28 | 0.31 | 0.20 | 0.19 | 0.23 | 0.26 | 0.29 | 0.33 | 0.23 |
| CP10 | 0.24 | 0.27 | 0.28 | 0.30 | 0.38 | 0.27 | 0.26 | 0.27 | 0.29 | 0.30 | 0.37 | 0.28 |
| $\Delta$MMMF | -0.15 | -0.19 | -0.23 | -0.27 | -0.31 | -0.19 | -0.12 | -0.16 | -0.20 | -0.24 | -0.20 | -0.16 |
| Onoff | 0.36 | 0.35 | 0.38 | 0.42 | 0.43 | 0.37 | 0.13 | 0.15 | 0.16 | 0.20 | 0.26 | 0.16 |
| DFY | 0.08 | 0.17 | 0.23 | 0.27 | 0.25 | 0.14 | 0.04 | 0.15 | 0.22 | 0.25 | 0.27 | 0.11 |
| DFR | -0.14 | -0.02 | -0.02 | 0.12 | 0.15 | -0.07 | -0.06 | -0.02 | 0.00 | 0.05 | 0.09 | -0.03 |
| IQ | 0.00 | 0.06 | 0.09 | 0.07 | 0.12 | 0.02 | -0.01 | 0.06 | 0.10 | 0.07 | 0.14 | 0.02 |
| DM | -0.06 | -0.09 | -0.08 | -0.17 | -0.13 | -0.07 | -0.04 | -0.07 | -0.05 | -0.15 | -0.10 | -0.05 |

Table 6. In-sample R-squares of predictive regressions using the extracted forecaster and multiple predictors

This table reports the in-sample R-square of predictive regressions using the univariate forecaster and multiple predictors used by Fama and French (1989) and Greenwood and Hanson (2013). The dependent variable is the corporate bonds future return in excess of one month Treasury bill rate. PLS uses the extracted forecaster by applying the partial least squares method to 26 individual predictors. FF uses the term spread (TMS) and default spread (DFY) as the predictors. GH uses the term spread (TMS), default spread (DFY), one month Treasury bill rate (TBL), lagged high-yield bond returns and issuance quality ratio (IQ) as the predictors. PCA uses the first one principal component of all variables as the predictor. $\Delta$ is the difference of in-sample R-squares of the predictive regressions using PLS and FF. In addition to the portfolios that include all (All), we sort all bonds independently into five rating portfolios (AAA, AA, A, BBB and Junk) and four maturity (Mat.) portfolios.

| | | Monthly(%) | | | | | Quarterly(%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Maturity | Rating | PLS | PCA | FF | GH | $\Delta$ | PLS | PCA | FF | GH | $\Delta$ |
| All | AAA | 8.07 | 0.19 | 2.06 | 0.73 | 6.01 | 9.19 | 0.37 | 4.85 | 3.49 | 4.34 |
| | AA | 9.38 | 0.42 | 4.48 | 2.72 | 4.91 | 13.20 | 0.79 | 9.40 | 6.88 | 3.80 |
| | A | 8.47 | 0.07 | 5.28 | 3.59 | 3.19 | 11.68 | 0.09 | 10.38 | 8.53 | 1.31 |
| | BBB | 10.50 | 0.29 | 7.25 | 5.04 | 3.25 | 14.57 | 0.56 | 14.72 | 11.38 | -0.15 |
| | Junk | 9.17 | 0.10 | 5.26 | 3.92 | 3.91 | 12.74 | 0.02 | 10.98 | 9.13 | 1.76 |
| | All | 9.04 | 0.25 | 3.92 | 2.29 | 5.12 | 11.45 | 0.47 | 8.52 | 6.37 | 2.93 |
| Short (2Yrs< Mat. <5Yrs) | AAA | 9.72 | 0.01 | 2.28 | 1.11 | 7.44 | 10.00 | 0.01 | 4.42 | 4.04 | 5.57 |
| | AA | 10.73 | 0.23 | 4.99 | 3.58 | 5.74 | 14.75 | 0.31 | 9.76 | 8.00 | 4.99 |
| | A | 9.26 | 0.00 | 5.99 | 4.78 | 3.28 | 12.42 | 0.01 | 10.33 | 9.28 | 2.09 |
| | BBB | 10.85 | 0.07 | 7.62 | 5.88 | 3.23 | 13.89 | 0.05 | 13.81 | 10.90 | 0.08 |
| | Junk | 8.64 | 0.04 | 4.60 | 3.30 | 4.05 | 13.36 | 0.12 | 11.47 | 8.94 | 1.89 |
| | All | 10.28 | 0.10 | 4.14 | 2.72 | 6.13 | 11.70 | 0.10 | 7.72 | 6.20 | 3.98 |
| 5Yrs< Mat. <7Yrs | AAA | 9.70 | 0.03 | 1.73 | 0.78 | 7.96 | 9.79 | 0.01 | 3.78 | 3.17 | 6.01 |
| | AA | 9.24 | 0.37 | 3.89 | 2.22 | 5.35 | 12.19 | 0.66 | 7.94 | 5.59 | 4.25 |
| | A | 9.11 | 0.05 | 5.30 | 3.94 | 3.81 | 11.79 | 0.04 | 9.36 | 7.93 | 2.42 |
| | BBB | 8.57 | 0.19 | 5.65 | 3.97 | 2.92 | 13.34 | 0.50 | 12.78 | 9.88 | 0.57 |
| | Junk | 8.75 | 0.02 | 4.70 | 3.33 | 4.05 | 15.30 | 0.02 | 11.94 | 10.09 | 3.35 |
| | All | 9.09 | 0.22 | 3.72 | 2.33 | 5.36 | 11.16 | 0.41 | 8.03 | 6.26 | 3.13 |
| 7Yrs< Mat. <10Yrs | AAA | 6.58 | 0.14 | 1.37 | 0.23 | 5.21 | 7.71 | 0.67 | 4.12 | 3.20 | 3.59 |
| | AA | 8.60 | 0.33 | 3.81 | 2.18 | 4.79 | 11.76 | 0.64 | 8.24 | 6.23 | 3.52 |
| | A | 8.00 | 0.05 | 5.05 | 3.35 | 2.95 | 11.31 | 0.05 | 10.60 | 8.92 | 0.70 |
| | BBB | 9.22 | 0.08 | 7.24 | 5.36 | 1.98 | 12.84 | 0.10 | 14.88 | 12.45 | -2.04 |
| | Junk | 8.09 | 0.08 | 1.15 | 0.26 | 6.94 | 8.95 | 0.25 | 5.04 | 3.82 | 3.91 |
| | All | 7.88 | 0.12 | 3.68 | 2.16 | 4.20 | 11.20 | 0.34 | 8.68 | 6.83 | 2.53 |
| Long (Mat. >10Yrs) | AAA | 6.29 | 0.14 | 1.99 | 0.63 | 4.30 | 9.89 | 0.79 | 6.71 | 4.94 | 3.18 |
| | AA | 7.03 | 0.63 | 3.61 | 1.79 | 3.42 | 11.85 | 1.38 | 8.47 | 5.83 | 3.38 |
| | A | 6.56 | 0.20 | 4.51 | 2.68 | 2.05 | 11.92 | 0.59 | 11.18 | 8.39 | 0.75 |
| | BBB | 8.01 | 0.53 | 5.45 | 3.75 | 2.56 | 13.76 | 1.61 | 13.47 | 10.97 | 0.30 |
| | Junk | 6.07 | 0.01 | 3.41 | 1.87 | 2.66 | 8.78 | 0.17 | 6.66 | 5.28 | 2.12 |
| | All | 7.92 | 0.36 | 3.54 | 1.81 | 4.38 | 12.37 | 1.02 | 9.81 | 7.25 | 2.57 |

Tbale 7. Out of sample R-squares of predictive regressions

This table reports the out-of-sample R squares of different predictive regressions. PLS uses the extracted forecaster by applying the partial least squares method to 26 individual predictors. FF uses term spread (TMS) and default spread (DFY) as predictors. GH uses the term spread (TMS), default spread (DFY), one month Treasury bill rate (TBL), lagged high-yield bond returns and issuance quality ratio (IQ) as the predictors. PCA uses the first principal component of all variables as the predictor. $\Delta$ is the difference in out-of-sample R squares of the forecast using PLS and FF. In addition to the portfolios that use all available bond price information (All), we sort all bonds independently into five rating portfolios (AAA, AA, A, BBB and Junk) and four maturity (Mat.) portfolios. The forecast imposes the non-negative sign restriction. 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). Standard errors are adjusted by the method of Hodrick (1992) to account for the impact of overlapping residuals. $^a$, $^b$, and $^c$ denote the significance level of 1%, 5%, and 10%, respectively.

| | | Monthly(%) | | | | | Quarterly(%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Maturity | Rating | PLS | PCA | FF | GH | $\Delta$ | PLS | PCA | FF | GH | $\Delta$ |
| All | AAA | $4.81^a$ | -0.47 | $1.60^a$ | $0.71^b$ | 3.21 | $4.57^b$ | -1.67 | $3.37^a$ | 1.05 | 1.20 |
| | AA | $9.41^a$ | 0.15 | $5.52^a$ | $2.79^a$ | 3.89 | $12.77^a$ | -0.58 | $10.41^a$ | $5.63^b$ | 2.36 |
| | A | $8.08^a$ | -1.38 | $4.86^a$ | $1.40^b$ | 3.22 | $9.47^a$ | -3.08 | $9.24^a$ | $4.40^c$ | 0.23 |
| | BBB | $9.98^a$ | -0.70 | $5.99^a$ | $1.51^b$ | 3.99 | $13.86^a$ | -2.06 | $13.42^a$ | $6.56^c$ | 0.43 |
| | Junk | $9.55^a$ | -0.32 | $4.23^a$ | $1.05^a$ | 5.32 | $12.24^a$ | -3.91 | $8.46^a$ | $2.83^b$ | 3.77 |
| | All | $7.32^a$ | -1.25 | $3.51^a$ | $0.71^b$ | 3.81 | $9.35^a$ | -3.50 | $7.36^a$ | $3.25^c$ | 1.99 |
| Short (2Yrs< Mat. <5Yrs) | AAA | $4.49^a$ | -2.32 | $1.14^a$ | $0.41^b$ | 3.35 | $5.06^a$ | -5.04 | $2.44^b$ | 0.93 | 2.62 |
| | AA | $11.79^a$ | -1.19 | $5.94^a$ | $3.25^a$ | 5.84 | $15.51^a$ | -3.74 | $10.46^a$ | $6.00^b$ | 5.04 |
| | A | $9.97^a$ | -2.22 | $5.47^a$ | $2.65^b$ | 4.50 | $10.93^b$ | -4.85 | $9.16^a$ | $5.54^c$ | 1.77 |
| | BBB | $11.53^a$ | -1.37 | $6.39^a$ | $2.14^c$ | 5.14 | $12.78^b$ | -4.18 | $12.14^b$ | $4.34^c$ | 0.64 |
| | Junk | $5.29^a$ | 0.15 | $2.37^a$ | -0.56 | 2.92 | $8.37^a$ | -0.57 | $7.20^a$ | -2.88 | 1.17 |
| | All | $7.64^a$ | -2.57 | $3.06^a$ | $0.13^a$ | 4.59 | $9.13^a$ | -6.62 | $5.16^a$ | $1.75^c$ | 3.96 |
| 5Yrs< Mat. <7Yrs | AAA | $3.20^a$ | -0.71 | $0.99^c$ | 0.16 | 2.21 | 3.53 | -2.65 | $0.82^a$ | -1.99 | 2.71 |
| | AA | $7.71^a$ | $0.15^c$ | $4.82^a$ | $2.06^b$ | 2.89 | $11.11^b$ | 0.34 | $9.14^b$ | 4.76 | 1.97 |
| | A | $7.16^a$ | -1.11 | $5.06^a$ | $1.25^c$ | 2.10 | $9.26^c$ | -2.58 | $8.71^a$ | 4.81 | 0.55 |
| | BBB | $8.34^a$ | -0.85 | $7.30^a$ | $2.30^b$ | 1.04 | $10.89^a$ | -0.54 | $10.22^a$ | 3.65 | 0.67 |
| | Junk | $2.64^a$ | -0.36 | -0.05 | -3.03 | 2.69 | $5.67^a$ | -3.12 | $5.00^a$ | $0.51^b$ | 0.68 |
| | All | $6.43^a$ | -1.31 | $3.97^a$ | $1.24^b$ | 2.46 | $9.34^a$ | -3.15 | $7.09^a$ | $3.38^c$ | 2.25 |
| 7Yrs< Mat. <10Yrs | AAA | $4.81^a$ | -0.47 | $1.60^b$ | 0.71 | 3.21 | $3.05^c$ | -0.57 | $3.07^a$ | $2.18^b$ | -0.01 |
| | AA | $9.41^a$ | 0.15 | $5.52^a$ | $2.79^b$ | 3.89 | $10.18^a$ | -0.61 | $9.12^a$ | $4.32^c$ | 1.06 |
| | A | $8.08^a$ | -1.38 | $4.86^a$ | $1.40^b$ | 3.22 | $9.66^b$ | -2.60 | $9.70^a$ | $4.59^c$ | -0.04 |
| | BBB | $9.98^a$ | -0.70 | $5.99^a$ | $1.51^b$ | 3.99 | $13.48^a$ | -2.12 | $15.50^a$ | $8.86^b$ | -2.02 |
| | Junk | $9.55^a$ | -0.32 | 4.23 | 1.05 | 5.32 | $4.53^b$ | -0.84 | $2.89^c$ | -2.32 | 1.64 |
| | All | $7.32^a$ | -1.25 | $3.51^a$ | $0.71^b$ | 3.81 | $10.21^a$ | -2.91 | $9.23^a$ | $4.28^b$ | 0.98 |
| Long (Mat. > 10Yrs) | AAA | $1.87^a$ | -0.28 | $1.49^b$ | -0.39 | 0.38 | $3.43^b$ | 0.83 | $5.93^a$ | -0.34 | -2.50 |
| | AA | $5.05^a$ | $0.71^b$ | $4.11^a$ | $1.71^b$ | 0.93 | $8.78^b$ | 0.85 | $8.58^a$ | $2.99^c$ | 0.20 |
| | A | $4.74^a$ | -0.27 | $4.00^a$ | $0.91^b$ | 0.74 | $9.70^a$ | -0.70 | $10.12^a$ | $3.77^b$ | -0.41 |
| | BBB | $5.73^a$ | $0.87^b$ | $4.04^a$ | $1.76^b$ | 1.69 | $11.04^a$ | $2.76^b$ | $9.29^a$ | $5.41^b$ | 1.75 |
| | Junk | $6.09^a$ | $2.59^a$ | $2.60^a$ | $0.33^b$ | 3.49 | $6.05^b$ | -1.27 | $5.06^a$ | -1.57 | 0.98 |
| | All | $5.42^a$ | -0.55 | $3.29^a$ | $0.36^c$ | 2.13 | $9.74^a$ | -1.21 | $9.12^a$ | $2.99^c$ | 0.62 |

Table 8. Utility gains

This table reports the annualized utility gains of different predictive regressions. PLS uses the extracted forecaster by applying the partial least squares method to 26 individual predictors. FF uses term spread (TMS) and default spread (DFY) as predictors. GH uses the term spread (TMS), default spread (DFY), one month Treasury bill rate (TBL), lagged high-yield bond returns and issuance quality ratio (IQ) as the predictors. PCA uses the first principal component of all variables as the predictor. $\Delta$ is the difference in utility gains using PLS and FF. In addition to the portfolios that include all bonds (All), we sort all bonds independently into five rating portfolios (AAA, AA, A, BBB and Junk) and four maturity (Mat.) portfolios. The forecast imposes the non-negative sign restriction.

| | | Monthly(%) | | | | | Quarterly(%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Maturity | Rating | PLS | PCA | FF | GH | $\Delta$ | PLS | PCA | FF | GH | $\Delta$ |
| All | AAA | 5.08 | -0.53 | 1.37 | 0.16 | 3.71 | 2.44 | -0.76 | 1.65 | -0.35 | 0.79 |
| | AA | 5.45 | -0.28 | 2.33 | -0.10 | 3.11 | 3.53 | -0.71 | 2.57 | 1.14 | 0.96 |
| | A | 4.20 | -1.86 | 1.74 | -1.11 | 2.46 | 3.38 | -1.65 | 1.29 | 0.70 | 2.09 |
| | BBB | 4.76 | -1.73 | 1.31 | -2.56 | 3.46 | 1.05 | -1.92 | 0.54 | -2.30 | 0.50 |
| | Junk | 5.85 | -1.42 | -0.72 | -3.66 | 6.57 | 4.18 | -2.46 | 0.32 | -0.53 | 3.86 |
| | All | 5.57 | -1.33 | 1.64 | -0.32 | 3.93 | 2.03 | -1.75 | 1.43 | 0.19 | 0.60 |
| Short (2Yrs< Mat. <5Yrs) | AAA | 1.87 | -2.90 | -0.77 | -0.38 | 2.64 | 0.60 | -2.23 | 0.27 | -0.81 | 0.33 |
| | AA | 4.64 | -1.67 | 0.51 | -0.35 | 4.14 | 3.15 | -1.41 | 1.90 | 0.45 | 1.25 |
| | A | 3.09 | -3.06 | 0.62 | -1.02 | 2.47 | 2.65 | -3.00 | 0.66 | -0.20 | 1.99 |
| | BBB | 5.03 | -2.36 | 1.14 | -1.70 | 3.89 | 1.27 | -3.09 | -0.17 | -2.87 | 1.44 |
| | Junk | 7.66 | 0.57 | 0.89 | -0.34 | 6.77 | 4.32 | 0.03 | 2.28 | 1.35 | 2.04 |
| | All | 3.44 | -2.89 | -0.67 | -1.35 | 4.11 | 1.17 | -2.66 | 0.30 | -1.16 | 0.88 |
| 5Yrs< Mat. <7Yrs | AAA | 3.44 | -1.43 | -1.58 | -1.63 | 5.02 | 1.60 | -1.46 | -1.75 | -1.22 | 3.35 |
| | AA | 4.44 | -0.10 | 1.75 | -0.98 | 2.69 | 2.81 | -0.28 | 2.19 | 1.03 | 0.62 |
| | A | 1.37 | -1.79 | -0.53 | -2.80 | 1.90 | 2.00 | -1.73 | 0.92 | 1.09 | 1.07 |
| | BBB | 1.44 | -0.95 | -1.56 | -4.75 | 3.01 | 0.03 | -1.14 | -1.64 | -4.23 | 1.67 |
| | Junk | 5.56 | -0.78 | -1.10 | -2.27 | 6.66 | 2.93 | -0.86 | 1.09 | -2.08 | 1.84 |
| | All | 4.78 | -1.46 | 1.23 | -0.59 | 3.55 | 2.07 | -1.46 | 0.91 | -0.09 | 1.17 |
| 7Yrs< Mat. <10Yrs | AAA | 3.60 | -0.94 | -0.36 | -0.56 | 3.95 | 1.57 | -0.74 | 0.37 | 0.33 | 1.20 |
| | AA | 4.92 | -0.32 | 2.11 | -0.98 | 2.81 | 3.56 | -0.50 | 2.47 | 0.87 | 1.10 |
| | A | 3.16 | -1.56 | -0.29 | -3.47 | 3.45 | 2.88 | -1.45 | 0.62 | 0.77 | 2.26 |
| | BBB | 4.17 | -1.44 | 2.73 | -0.83 | 1.43 | 2.40 | -1.31 | 1.72 | -1.75 | 0.69 |
| | Junk | 1.69 | 0.20 | -3.10 | -4.71 | 4.78 | 0.99 | 0.11 | -2.04 | -0.48 | 3.02 |
| | All | 5.27 | -1.46 | 1.91 | -0.56 | 3.36 | 3.23 | -1.08 | 2.38 | 0.61 | 0.85 |
| Long (Mat. > 10Yrs) | AAA | 1.87 | -0.67 | -0.51 | -2.30 | 2.38 | 1.12 | -0.43 | 0.76 | -0.71 | 0.36 |
| | AA | 3.40 | -0.06 | 1.46 | -1.75 | 1.95 | 2.39 | -0.30 | 2.46 | 0.89 | -0.07 |
| | A | 2.11 | -0.92 | -0.82 | -3.00 | 2.93 | 1.77 | -1.07 | 0.30 | -0.20 | 1.48 |
| | BBB | 4.69 | 0.15 | -0.27 | -4.11 | 4.96 | 2.60 | 0.05 | 1.17 | -2.41 | 1.43 |
| | Junk | 0.30 | 0.87 | -1.41 | -4.59 | 1.71 | 2.31 | -0.89 | -1.48 | 0.50 | 3.79 |
| | All | 5.20 | -0.90 | 1.45 | -2.40 | 3.75 | 3.94 | -0.31 | 2.96 | -0.11 | 0.98 |

Table 9. Forecast encompassing tests

This table reports the $p$-values of the Harvey, Leybourne and Newbold (1998) statistic for the out-of-sample forecast of monthly corporate bond excess return. The statistic provides a one-sided test of the null hypothesis that the out-of-sample forecast based on Model 1 encompasses the out-of-sample forecast based on Model 2, against the alternative hypothesis that the out-of-sample forecast based on Model 1 does not encompass the out-of-sample forecast based on Model 2. PLS uses the extracted factor applying the partial least squares method to 26 individual predictors. FF uses the term spread (TMS) and default spread (DFY) as the predictors. GH uses the term spread (TMS), default spread (DFY), one month Treasury bill rate (TBL), lagged high-yield bond returns and issuance quality ratio (IQ) as the predictors. PCA uses the first one principal component of all variables as the predictor.

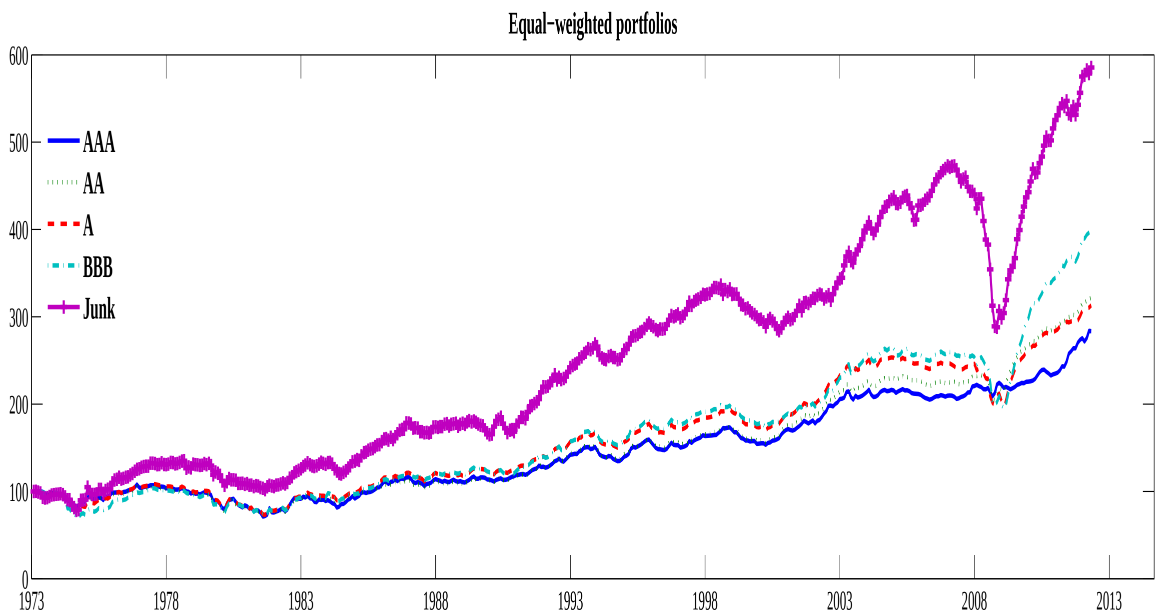
| | | | Rating | | | | | |
|---|---|---|---|---|---|---|---|---|
| Maturity | Model1 | Model 2 | AAA | AA | A | BBB | Junk | All |
| All | PLS | FF | 0.30 | 0.39 | 0.42 | 0.46 | 0.60 | 0.41 |
| | PLS | GH | 0.57 | 0.65 | 0.78 | 0.74 | 0.93 | 0.89 |
| | PLS | PCA | 0.23 | 0.53 | 0.64 | 0.51 | 0.51 | 0.36 |
| | FF | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | GH | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | PCA | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Short (2Yrs< Mat. <5Yrs) | PLS | FF | 0.09 | 0.34 | 0.43 | 0.56 | 0.52 | 0.21 |
| | PLS | GH | 0.41 | 0.88 | 0.81 | 0.84 | 0.94 | 0.89 |
| | PLS | PCA | 0.08 | 0.40 | 0.69 | 0.61 | 0.49 | 0.12 |
| | FF | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 |
| | GH | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | PCA | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 5Yrs< Mat. <7Yrs | PLS | FF | 0.41 | 0.23 | 0.33 | 0.29 | 0.27 | 0.32 |
| | PLS | GH | 0.51 | 0.46 | 0.62 | 0.58 | 0.43 | 0.83 |
| | PLS | PCA | 0.24 | 0.37 | 0.57 | 0.17 | 0.44 | 0.27 |
| | FF | PLS | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| | GH | PLS | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| | PCA | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 7Yrs< Mat. <10Yrs | PLS | FF | 0.16 | 0.22 | 0.25 | 0.06 | 0.25 | 0.21 |
| | PLS | GH | 0.21 | 0.47 | 0.52 | 0.36 | 0.59 | 0.58 |
| | PLS | PCA | 0.17 | 0.38 | 0.49 | 0.24 | 0.24 | 0.34 |
| | FF | PLS | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 | 0.00 |
| | GH | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | PCA | PLS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Long (Mat. > 10Yrs) | PLS | FF | 0.12 | 0.14 | 0.18 | 0.20 | 0.17 | 0.20 |
| | PLS | GH | 0.24 | 0.07 | 0.33 | 0.06 | 0.38 | 0.53 |
| | PLS | PCA | 0.21 | 0.35 | 0.44 | 0.15 | 0.21 | 0.26 |
| | FF | PLS | 0.05 | 0.02 | 0.04 | 0.01 | 0.00 | 0.00 |
| | GH | PLS | 0.02 | 0.02 | 0.01 | 0.05 | 0.00 | 0.00 |
| | PCA | PLS | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table 10. Out-of-sample forecasts for different regimes

This table reports the out-of-sample R-squares of monthly return forecasts using the extracted univariate forecaster (PLS) during good, normal and bad growth periods between 1983 and 2010. Following Rapach, Strauss and Zhou (2010), good, normal and bad growth regimes are based on the sorted real GDP growth rates. The forecast accounts for the non-negative sign restriction. 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.

| Maturity | GDP | AAA | AA | A | BBB | Junk | ALL |
|---|---|---|---|---|---|---|---|
| | Good | $2.95^b$ | $2.82^b$ | $4.02^a$ | $4.29^a$ | $7.30^a$ | $3.41^b$ |
| All | Normal | $6.20^a$ | $13.40^a$ | $13.32^a$ | $16.93^a$ | $14.87^a$ | $11.35^a$ |
| | Bad | $6.31^a$ | $13.45^a$ | $8.52^b$ | $10.51^a$ | $8.76^a$ | $8.83^a$ |
| | Good | $3.71^a$ | $4.24^a$ | $8.35^a$ | $7.09^a$ | -0.56 | $6.19^a$ |
| Short | Normal | $4.46^a$ | $15.08^a$ | $12.01^a$ | $25.48^a$ | $20.95^a$ | $10.85^a$ |
| | Bad | $5.38^a$ | $16.79^a$ | $10.11^b$ | $9.32^b$ | $4.01^a$ | $6.85^a$ |
| | Good | $4.34^b$ | $3.20^b$ | $3.42^b$ | $2.33^b$ | $4.18^a$ | $3.59^b$ |
| 5Yrs<Mat.<7Yrs | Normal | $2.56^c$ | $10.48^a$ | $9.21^a$ | $15.57^a$ | $9.92^b$ | $10.01^a$ |
| | Bad | $6.64^b$ | $10.99^a$ | $9.65^b$ | $7.02^a$ | $4.42^a$ | $7.59^a$ |
| | Good | $2.33^c$ | $2.19^b$ | $3.89^b$ | $3.77^b$ | $4.35^a$ | $2.99^b$ |
| 7Yrs<Mat.<10Yrs | Normal | $3.20^b$ | $13.59^a$ | $14.71^a$ | $12.25^a$ | -1.05 | $12.73^a$ |
| | Bad | $4.27^b$ | $9.29^a$ | $5.68^c$ | $9.81^a$ | $3.61^b$ | $5.34^b$ |
| | Good | -0.69 | $3.39^b$ | -0.04 | $0.80^c$ | -4.06 | $1.14^b$ |
| Long | Normal | $6.60^a$ | $10.02^a$ | $13.76^a$ | $5.92^a$ | $16.02^a$ | $12.35^a$ |
| | Bad | 1.20 | $2.87^c$ | $3.40^b$ | $10.69^a$ | $7.38^a$ | $4.82^b$ |

Figure 1.Return indices by rating
This graph plots the excess return indices of rating portfolios.



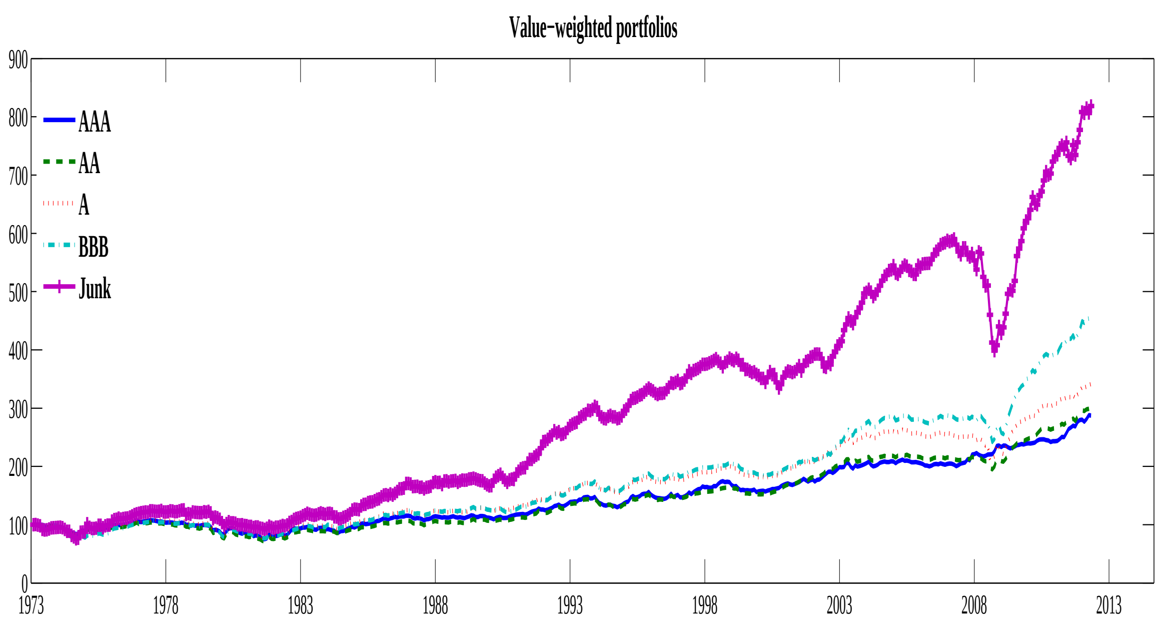



Figure 2. Extracted univariate forecaster
This figure plots the monthly series of extracted forecaster by applying the partial least squares method to 26 individual predictors (PLS).

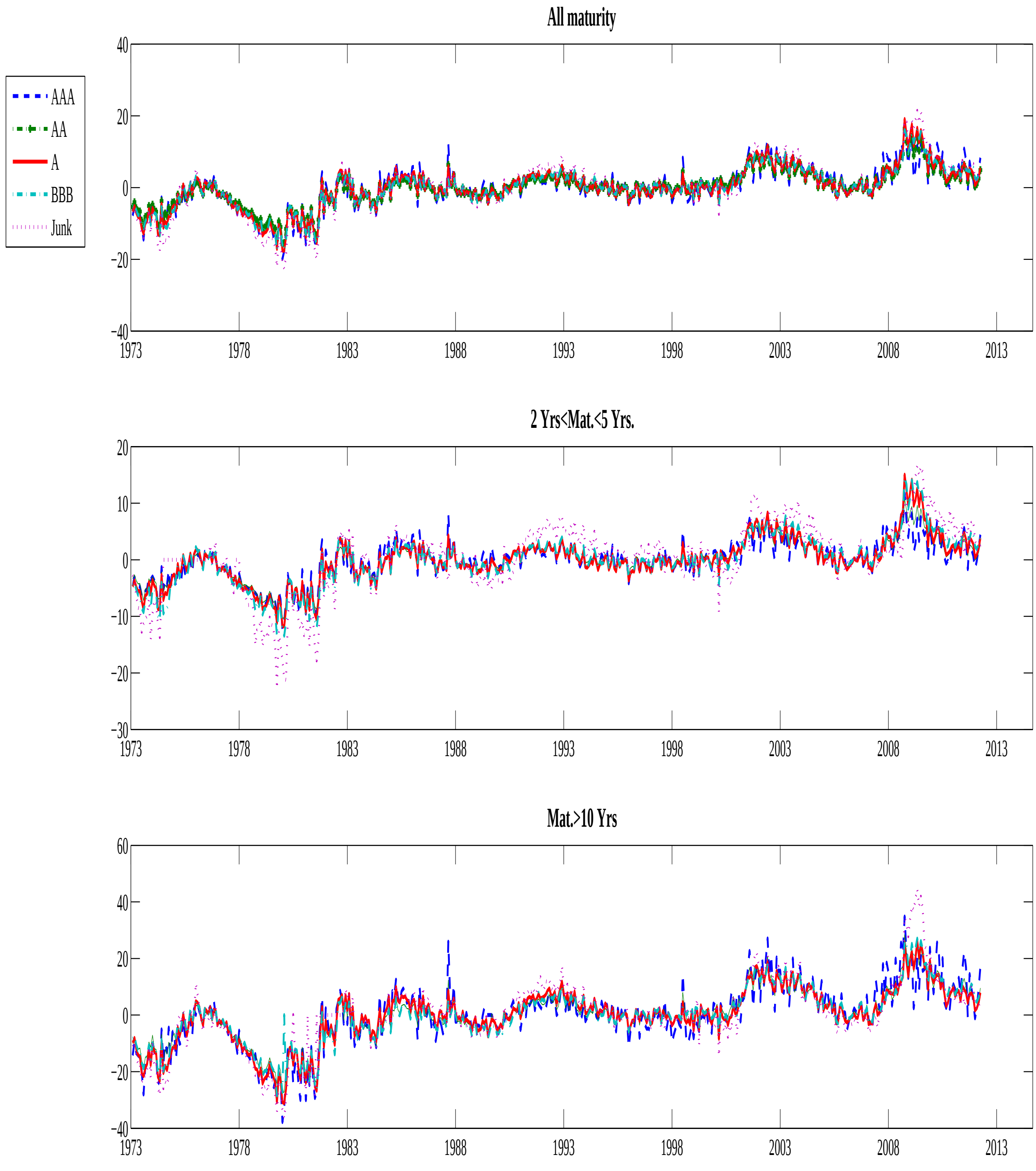


Figure 3. Predicted returns and ex post returns for rating portfolios
This figure plots ex post monthly value-weighted portfolio returns and predicted returns by historical mean (HM) and the model using the extracted forecaster (PLS).

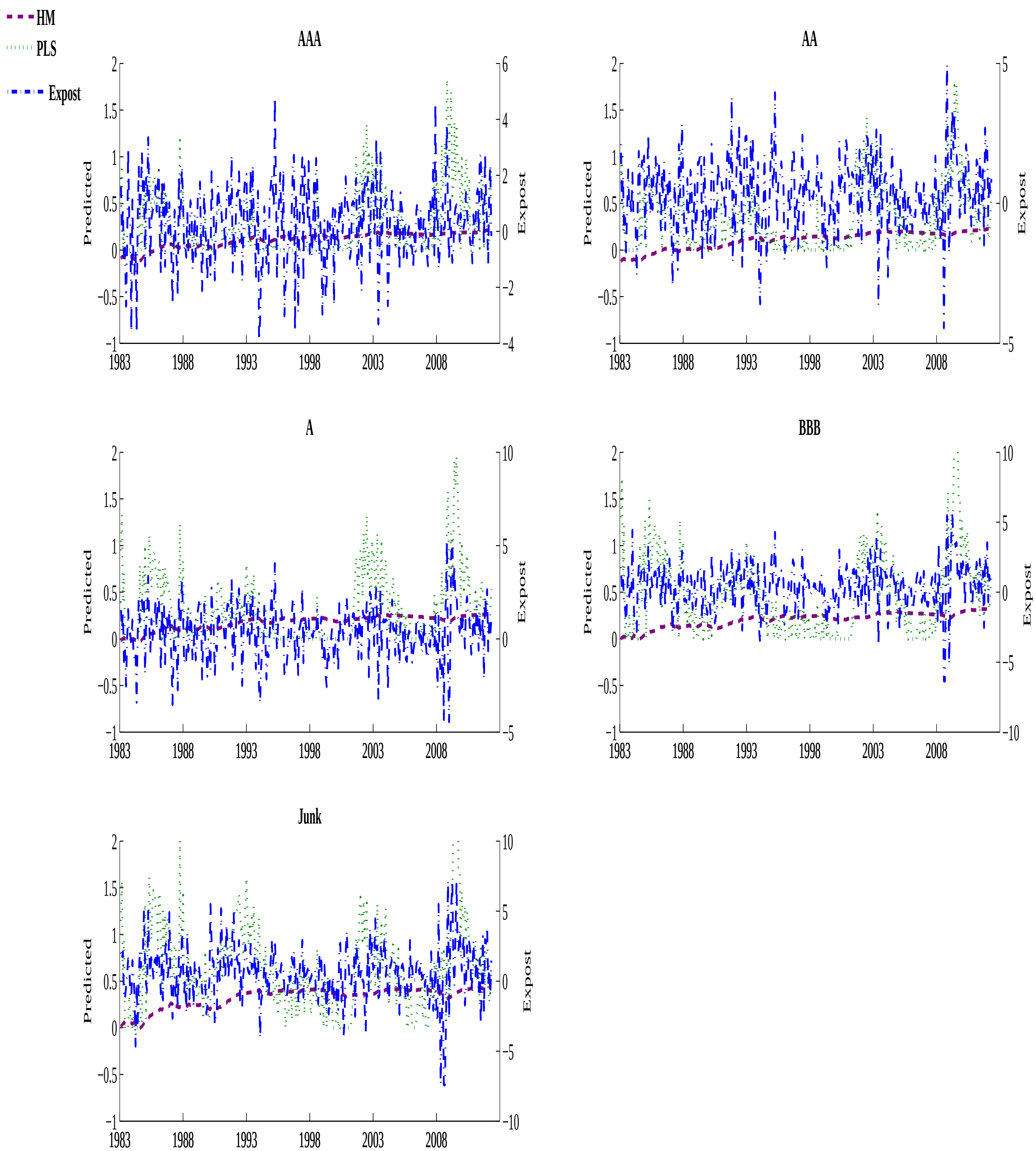


Figure 4. Predicted return and ex post returns for the maturity portfolios in each rating
This figure plots ex post monthly value-weighted portfolio returns and predicted returns by historical mean (HM) and the model using the extracted univariate forecaster (PLS). Short-maturity portfolios are constructed by bonds with maturity between two and five years. Long-maturity portfolios are constructed by bonds with maturity greater than ten years.

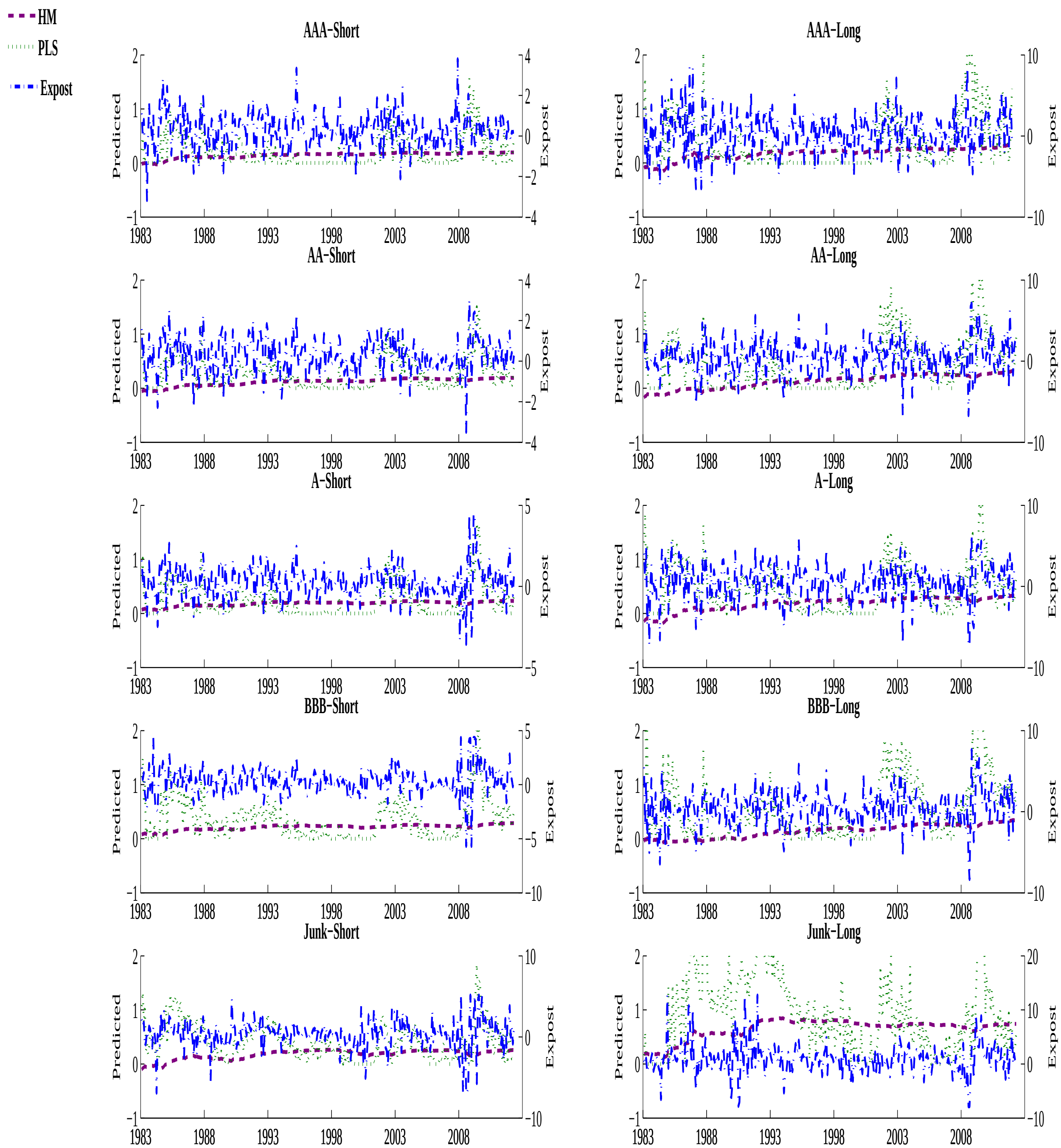


Figure 5. Mean predicted returns
This figure plots the mean of value-weighted portfolio returns predicted by the extracted univariate forecaster (PLS) for horizons of one month, one quarter, one year, two years, three years and four years.

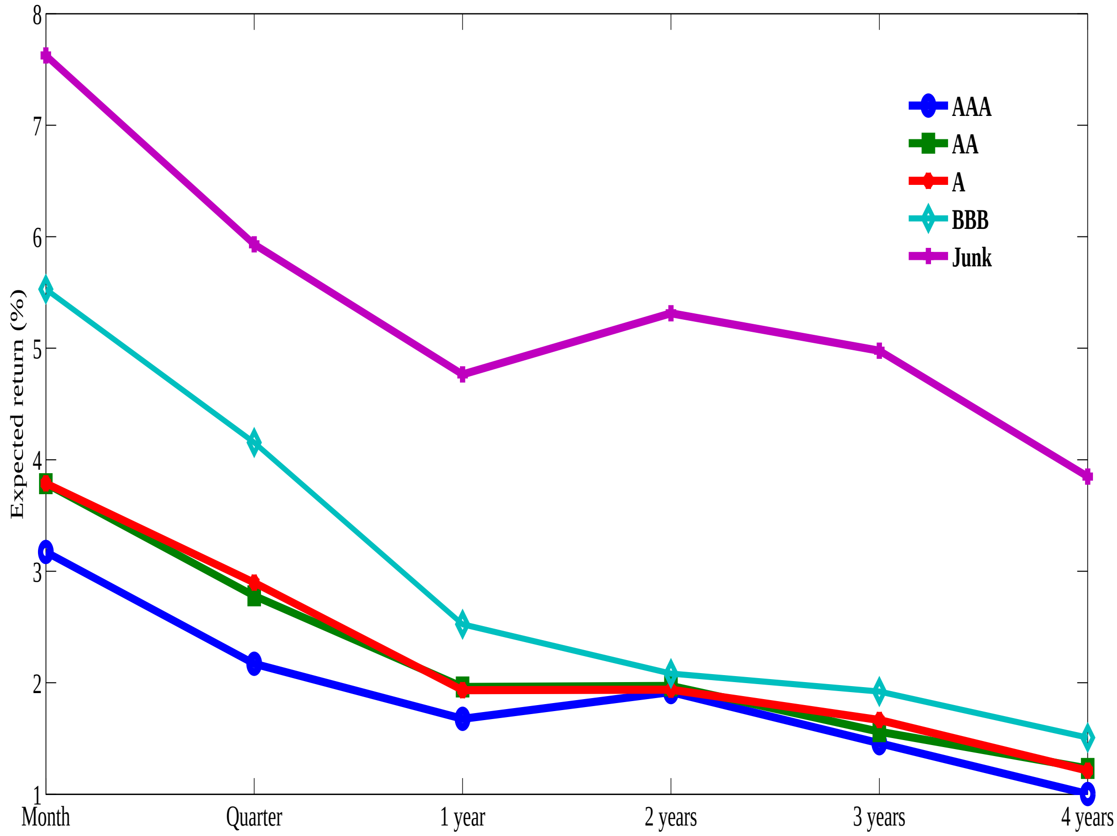


Figure 6. Predicted returns at NBER peaks and troughs
This figure plots the mean of value-weighted portfolio returns at NBER peaks (July 1990, March 2001 and December 2007) and troughs (March 1991, November 2001 and June 2009) predicted by the extracted forecaster (PLS) for horizons of one month, one quarter, one year, two years, three years and four years.