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Predictions of corporate bond excess returns ☆

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ABSTRACT

In this paper, we investigate the predictability of corporate bond excess returns using a comprehensive data sample for the period from January 1973 to December 2010. We find that corporate bond returns are more predictable than stock returns, and the predictability tends to be higher for low-grade bonds and short-maturity bonds. A forward rate factor captures substantial variations in expected bond excess returns. Furthermore, liquidity factors and a bond's credit spread have predictive power on corporate bond excess returns. Combining these variables with traditional predictors significantly improves the performance of the predictive model for corporate bond returns.

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1. Introduction

The predictability of asset returns has attracted considerable attention of financial economists. Whether returns are predictable remains a subject of ongoing debates.[3] The literature focuses on the predictability of stock market returns. At the same time, the issue of return predictability is relatively underexplored for the corporate bond market. In this paper, we examine the predictability of corporate bond returns using a large individual bond sample, additional predictors, and improved empirical methods advanced in the recent literature.

Investigating the predictability of returns on the corporate bond market is important for various reasons. First and foremost, understanding the predictability of returns is necessary for a market whose size is roughly equal to that of equities in aggregate value, from the perspective of risk premium determination. More importantly, the study of bond return predictability provides clues for the sources of variations in expected returns and directly answers the question of whether returns on different classes of assets are driven by common factors. Corporate bonds are in many ways different from stocks. Bond analysis offers additional evidence to compare and contrast the results to the equity and other markets. Further, as variations in expected returns affect investors' asset allocations, understanding the predictability of returns in different asset classes is essential for developing optimal strategies for dynamic asset allocation and hedging.

In investigating the predictability of corporate bond returns, our analysis draws on several important papers. Cochrane and Piazzesi (2005) find that Treasury excess returns can be predicted by the full term structure of forward rates. We examine whether the Cochrane-Piazzesi forward rate factor can predict corporate bond returns. Gilchrist and Zakrajsek (2012) find that a credit spread index extracted from corporate bonds predicts future economic activity. Their finding implies that the credit spread can have predictive power for expected corporate bond returns as bond premiums vary with economic conditions. We include the bond's credit spread as an additional predictor for corporate bond returns. Bongaerts, De Jong, and Driessen (2012) and Dick-Nielsen, Feldhutter, and Lando (2012) document that credit spreads contain a significant liquidity component. In this paper, we consider a number of conventional liquidity indices, as well as the corporate bond liquidity index suggested by Dick-Nielsen, Feldhutter, and Lando (2012) to explore the predictive power of these indices for corporate bond returns.

Using a comprehensive data sample of corporate bonds, we provide several unique findings that expand the literature on return predictability. First, we find that corporate bond returns are more predictable than stock returns, and the magnitude of predicted bond returns is of economic significance. Returns tend to be more predictable for speculative-grade bonds and short-maturity bonds.

Second, we find that the Cochrane-Piazzesi (2005) forward rate factor, liquidity factors, and the bond's credit spread have predictive power for corporate bond returns. Including these variables significantly improves the forecasting performance of the predictive model. Variations in expected returns tracked by these predictors are linked to business cycles and market liquidity conditions. The results show that the predictability of corporate bond returns is driven predominantly by time-varying risk premiums associated with changing business conditions.

Third, we find that a combination of individual forecasts generates better out-of-sample forecasting performance than single forecasts for corporate bond returns by improving the information content of the model and stability of out-of-sample forecasting. Different predictors track different components of expected corporate bond returns. A combination of individual predictive models out-of-sample captures different dimensions of evolving return information and

[3] See, for example, Ang and Bekaert (2007), Campbell and Thompson (2008), Welch and Goyal (2008), Rapach, Strauss, and Zhou (2010), and Thornton and Valente (2012). Past studies have shown that stock returns can be predicted by long and short bond rates (Campbell, 1987; Ang and Bekaert, 2007), default and term spreads (Fama and French, 1989), dividend yields (Fama and French, 1988, 1989; Cochrane, 1992, 2008), valuation ratios (Campbell and Thompson, 2008), earnings yields (Campbell and Shiller, 1988), earnings (Sadka and Sadka, 2009), book-to-market ratio (Kothari and Shanken, 1997), inflation rates (Fama and Schwert, 1977), stock market volatility (Guo, 2006), and consumption-to-wealth ratio (Lettau and Ludvigson, 2001). Fama and Bliss (1987) find that the spread between the forward rate and the one-year spot rate predicts Treasury returns.

therefore, provides more reliable forecasts and consistently outperforms the historical average forecast of the bond risk premium.

Researchers have documented the predictability of corporate bond returns. Keim and Stambaugh (1986) examine return predictability and find that long-term bond returns with different default risks can be predicted by variables that reflect the levels of bond and stock prices. Fama and French (1989) examine the issue of whether corporate bond returns can be forecasted by the factors that predict stock returns. They document evidence of co-movements in expected returns on corporate bonds and stocks, and both returns can be predicted by common factors such as dividend yields, default spreads, and term spreads.[4] Chang and Huang (1990) find that the level and slope of term structure and the spread between the long-term Baa bond yield and the one-month Treasury bill rate can predict long-term corporate bond returns. Using the method of maximizing predictability across portfolios, Lo and MacKinlay (1997) confirm that corporate bond index returns can be predicted by variables similar to those suggested by Keim and Stambaugh (1986) and Fama and French (1989). Baker, Greenwood, and Wurgler (2003) find that the maturity of new debt issues has predictive power for excess bond returns.

Our paper contrasts these papers by examining the predictability of the credit spread component of corporate bond returns. Our focus on this return component is related to several studies (Clinebell, Kahl, and Stevens, 1996; Ilmanen, 2010; Haesen and Houweling, 2012). The study by Haesen and Houweling (2012) is most closely related to ours. Like their study, we examine the predictability of corporate bond returns in excess of the duration-matched Treasury bond yields. This approach allows us to investigate the predictability of credit spread returns, which are the most important component of corporate bond returns. Our paper differs from Haesen and Houweling (2012) in several major aspects. First, our paper is distinguished from theirs in terms of data and empirical methodology. We use individual bond data in empirical tests to have better control over bond characteristics and provisions. In addition, we employ the combination forecast method and encompassing tests to assess the predictive power of different variables. Second, we explore different forecasters in the predictive model. We show that forward rate, liquidity factors,[5] and portfolio credit spreads have predictive power for corporate bond returns. By contrast, Haesen and Houweling (2012) find that changes in implied equity volatility and the Halloween indicator can predict corporate bond excess returns besides the traditional variables in the literature (e.g., Keim and Stambaugh, 1986; Fama and French, 1989; Fuller and Kling, 1994; Clinebell, Kahl, and Stevens,1996; Rapach and Wohar, 2002). Our study thus complements their work in expanding the set of predictors that can predict corporate bond returns. Third, we examine the significance of out-of-sample predictability of corporate bond returns by accounting for the risk borne by investors in return forecasts.

Our paper is also related to several other recent papers on the predictability of corporate bond returns (Hong, Lin, and Wu, 2012; Greenwood and Hanson, 2013; Lin, Wu, and Zhou, 2013; Nozawa, 2013). Our paper differs from these papers in terms of the empirical approach, data, and selection of predictors. Hong, Lin, and Wu (2012) use a time series approach to forecasting corporate bond index returns and address the issue of nonlinearity in the predictive relation. They find that past corporate bond and stock returns can predict corporate bond index returns. Greenwood and Hanson (2013) show that the credit quality of debt issuers can forecast corporate bond returns. Lin, Wu, and Zhou (2013) use the partial least squares (PLS) method of Kelly and Pruitt (2012, 2013) to extract a single forecaster from various variables including macroeconomic factors and find that it has predictive power for corporate bond returns. Nozawa (2013) shows that bonds with past low prices relative to Treasury bonds with the same maturity earn higher returns in a way resembling reverse momentum. Unlike these studies, we examine the predictability of the credit spread component of corporate bond returns using different predictors and employ the combination forecast method in out-of-sample forecasts.

[4] Sangvinatsos (2005) also documents corporate bond index return predictability using dividend yields, term premiums, and default premiums.

[5] The liquidity factor is important in asset pricing (e.g., Amihud, 2002; Pastor and Stambaugh, 2003; Sadka, 2006, 2010; Bao, Pan, and Wang, 2011; Lin, Wang, and Wu, 2011; Næs, Skjeltorp, and Odegaard, 2011; Dick-Nielsen, Feldhutter, and Lando, 2012).

The remainder of this paper is organized as follows. In Section 2, we discuss the empirical methodology and forecasting variables for corporate bond returns. In Section 3, we describe the data and in Section 4 report the results of in-sample regressions. In Section 5, we present out-of-sample forecasts and robustness checks. Finally, in Section 6 we summarize the main findings and conclude the paper.

2. Empirical methodology

In this section, we outline the model and methods for evaluating the forecasting performance. We use the conventional test of equity return predictability to regress future returns on explanatory variables known at current time. This predictive regression framework is cast on corporate bond returns:

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

where r_{t+1} is the return of corporate bonds in excess of the duration-matched Treasury rate, x_t is a vector of explanatory variables, and ε_{t+1} is an error term.

Two desirable explanatory variables are term and default spreads. Expected returns on corporate bonds can change through time due to variations in either maturity or default premiums. Interest rate uncertainty has a direct effect on maturity premiums. Short-term rates are more volatile than long-term rates and the spread between long- and short-term rates reflects interest rate uncertainty. The variation in default spreads is closely linked to changes in business conditions, which affect the probability of firm survivals. The default spread widens when the economy is poor as investors require a larger premium.

Another candidate is the dividend yield, which has been shown to have the ability to forecast stock returns. Fama and French (1989) find that dividend yields also have forecast power for bond returns. Dividend yields and default spreads are positively correlated. Like default spreads, dividend yields reflect time variations in expected returns to changes in business conditions.

Cochrane and Piazzesi (2005), hereafter CP find that a single factor constructed from a linear combination of forward rates has high predictive power for Treasury bond returns. They show that this factor cannot be captured by the popular yield curve factors of level, slope, and curvature. As their study did not cover corporate bonds, it is unclear about the predictive role of this forward rate factor for risky bond returns.[6] We examine the predictive power of the CP forward rate factor for returns of bonds with different ratings and maturities.

There is substantial evidence that expected bond returns contain a liquidity premium component.[7] Næs, Skjeltorp, and Odegaard (2011) find that changes in stock market liquidity can predict future economic performance. This finding implies that changes in aggregate liquidity can track variations in expected stock returns associated with changing business conditions. Given that illiquidity is a greater concern for corporate bonds than for stocks, changes in aggregate liquidity may have predictive power for corporate bond returns. Liquidity is a main dimension that can potentially cause a disconnect between corporate bonds and other markets, which can give rise to a different predictive return pattern for corporate bonds. In this paper, we investigate the predictive ability of various liquidity variables for corporate bond returns.

Moreover, the yield on the bond itself reflects the future risk premium and thus may have additional predictive power beyond the default spread.[8] Greenwood and Hanson (2013) provide evidence consistent with this argument[9] and Gilchrist and Zakrajsek (2012) show that credit spreads

[6] Thornton and Valente (2012) find counter evidence that the CP factor does not have good out-of-sample forecasting ability for Treasury bond returns. It is unclear whether this may also happen to corporate bonds.

[7] See Bao, Pan, and Wang (2011), Bongaerts, De Jong, and Driessen (2012), Dick-Nielsen, Feldhutter, and Lando (2012), and Friewald, Jankowitsch, and Subrahmanyam (2012). Buhler and Trapp (2010) show that bond liquidity premium is time varying.

[8] We thank an anonymous referee for making this suggestion.

[9] However, unlike our study, Greenwood and Hanson (2013) use past bond returns instead of yield spreads.

can predict economic activity. To explore the role of the bond's spread, we calculate the rating and duration portfolio's credit spread and use it as a predictor.

2.1. Empirical tests

The performance of predictive regressions in (1) is evaluated over different return horizons. The in-sample standard errors are adjusted by the Hodrick (1992) method to account for the impact of overlapping residuals when the predictive horizon is beyond one month. In addition, we use the method suggested by Murphy and Topel (1985) to account for parameter uncertainty in the two-step regression estimation when using the CP factor as a predictor. For the out-of-sample test, we estimate the parameters of the predictive regression model recursively, where parameters are estimated using all available information up to t to forecast excess returns at $t+1$. We use the same method to calculate the historical average under the hypothesis that returns follow the random walk with a drift. So, historical mean returns are also updated each period (month).

The parameters estimated by the predictive regression can be subject to small sample biases of significant magnitude. This issue is particularly worrisome when predictors are persistent and when past regression disturbances are correlated with the predictors. As such, there can be substantial size distortions with the standard t-statistic, resulting in a tendency to over reject the null of no predictability. Kandel and Stambaugh (1996) and Connor (1997) suggest imposing an information prior in the distribution of parameter estimates to adjust least squares estimates. In a Bayesian framework, this prior produces a posterior of parameter estimates that is a product of the ordinary least squares (OLS) estimates and a shrinking factor reflecting the precision of parameter estimates. Following Connor (1997), we adjust OLS parameter estimates in the predictive regression as follows:

$$\hat{\beta}_{j,Bayes} = \left[\frac{T}{T+(1/\rho_j)}\right]\hat{\beta}_{j,OLS}, \tag{2}$$

where the shrinking factor in the brackets is a function of the sample size T and a parameter $\rho_j = E[R_j^2/1-R^2]$, R_j^2 is the marginal R^2 of variable j, and R^2 is the coefficient of determination in the regression that may include multiple predictors.

Campbell and Thompson (2008) impose weak restrictions on the signs of coefficients and excess return forecasts. The rationale is that in theory the risk premium should be positive. The sign restriction minimizes the impact of perverse results on out-of-sample forecasts when a regression is estimated over a short sample period. They find evidence that this procedure improves the out-of-sample performance. As our bond sample period is shorter than their stock counterpart, perversity is a potential concern. To address this concern, we impose similar restrictions on out-of-sample forecasts of bond returns; that is, the sign of the coefficient is restricted to be consistent with the theory and the forecast of bond premium is set to zero whenever it is negative.[10]

To evaluate the out-of-sample performance, we calculate the following R^2 statistic:

$$R_{OS}^2 = 1 - \frac{\sum_{t=1}^{T-k}(r_{t+k}-\hat{r}_{t+k})^2}{\sum_{t=1}^{T-k}(r_{t+k}-\overline{r}_{t+k})^2}, \tag{3}$$

where r_{t+k} is the realized excess 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 is the sample size, t indicates the time that the forecast is made, and k is the number of periods ahead in the forecast. R_{OS}^2 measures the improvement in mean square prediction errors (MSPE) for the predictive regression model over the historical average forecast out of sample. When $R_{OS}^2 > 0$, the predictive regression forecast outperforms the historical average forecast.

We test the significance of R_{OS}^2 using 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 prediction (updated each period) and the predictive regression are equal, against the

[10] We also examine the model performance without these restrictions and find that our results are robust to sign restrictions.

alternative that the predictive regression model has lower square prediction errors than the historical average forecast method. To calculate the MSPE-adjusted statistic, we first compute the following square error difference:

$$e_{t+k} = (r_{t+k} - \overline{r}_{t+k})^2 - [(r_{t+k} - \hat{r}_{t+k})^2 - (\overline{r}_{t+k} - \hat{r}_{t+k})^2]. \tag{4}$$

By regressing e_{t+k} on a constant, the t-statistic gives a p-value for the one-sided (upper tail) test under the standard normal distribution. Standard errors are adjusted by the Hodrick (1992) method to account for the impact of overlapping residuals when the out-of-sample forecast horizon is longer than a month.

Rapach, Strauss, and Zhou (2010) show that combining individual forecasts significantly improves the out-of-sample forecast for the equity premium by reducing the impact of model uncertainty and instability in forecasting ability of individual predictors. We use this method to generate out-of-sample bond return forecasts and compare them with the results of individual forecasts. Given N individual predictors, we have N out-of-sample forecasts from predictive regressions, denoted by $\hat{r}_{i,t+k}$, $i = 1, 2, \ldots, N$. The combination forecast of r_{t+k} at time t is the weighted averages of N individual forecasts:

$$\hat{r}_{c,t+k} = \sum_{i=1}^{N} \omega_{i,t} \hat{r}_{i,t+k}, \tag{5}$$

where $\omega_{i,t}$ is the weight for combining individual forecasts. In empirical investigations, we focus on mean and median combination forecasts, which have been shown to perform as well as more complicated weighting schemes (see Rapach, Strauss, and Zhou, 2010).

To assess whether adding new explanatory variables, such as the forward rate factor, liquidity factors, and the bond's credit spread, significantly improves the predictive power of the traditional model, we use the test method of Harvey, Leybourne, and Newbold (1998). The null hypothesis is that the model i forecast encompasses the model j forecast (e.g., with additional predictors), against the one-sided alternative hypothesis that the former does not encompass the latter. Let $d_{t+k} = (\hat{u}_{i,t+k} - \hat{u}_{j,t+k})\hat{u}_{i,t+k}$, 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

$$MHLN = \frac{(T-k-1)}{(T-k)} \left[\hat{V}(\overline{d})^{-1/2} \right] \overline{d}, \tag{6}$$

where $\overline{d} = (1/T-k)\Sigma_{t=1}^{T-k} d_{t+k}$, $\hat{V}(\overline{d}) = (T-k)^{-1}\hat{\phi}_0$, $\hat{\phi}_0 = (T-k)^{-1}\Sigma_{t=1}^{T-k}(d_{t+k} - \overline{d})^2$ and MHLN has a t distribution with $T-k-1$ degree of freedom. We further adjust standard errors by the Hodrick (1992) method to account for the effect of overlapping residuals over different forecast horizons. The MHLN test determines whether additional predictors contribute significantly to the power of the predictive model after controlling for the effects of other predictors.

2.2. *Economic significance*

In out-of-sample regressions, R^2 values are typically small and this raises a concern about their economic significance. To address this concern, we use a measure of utility gains (or certainty equivalent returns) to assess the economic significance of the return predictability, which account for parameter uncertainty and dynamic allocation.[11]

A number of studies use a measure of realized utility gains for a mean-variance investor calculated from the out-of-sample forecast to gauge the economic significance of stock return predictability (e.g., Marquering and Verbeek, 2004; Welch and Goyal, 2008; Campbell and Thompson, 2008; Wachter and Warusawitharana, 2009). This measure addresses the risk borne by an investor and is therefore quite suitable for gauging the economic significance of risky bond return forecasts.

[11] Besides the utility gain measure, we calculated mean-variance performance measures for economic significance (Sangvinatsos and Wachter, 2005) and the risk-adjusted abnormal return of the predictive model relative to historical mean suggested by Goetzmann et al. (2007), GISW. Our results are robust to different performance measures.

The utility measure is derived from the portfolio allocations based on either the naïve historical average forecast or the predictive model forecast. A mean-variance investor who forecasts the risk premium using a model j will decide at t to allocate a proportion of the portfolio $w_{j,t} = (1/\gamma)(\hat{r}_{j,t+1}/\hat{\sigma}^2_{t+1})$ to risky bonds at $t+1$, where $\hat{\sigma}^2_{t+1}$ is the estimate of the variance of bond excess returns, γ is the risk aversion coefficient, and $j=h$ or p, which represents the return forecast using the historical mean and the predictive model, respectively.[12] If the investor uses the historical mean to forecast returns, we have $\hat{r}_{h,t+1} = \bar{r}_{t+1}$, the historical average return, and for that using a predictive model, the forecast return is denoted by $\hat{r}_{p,t+1}$.

We use the rolling-window method to estimate the variance at $t+1$. The rolling-window method uses a fixed window of past return observations to estimate the variance. We select a 10-year rolling window to estimate the variance at $t+1$:

$$\hat{\sigma}^2_{t+1} = \frac{1}{120}\sum_{j=0}^{119}\left(r_{t-j} - \frac{1}{120}\sum_{j=0}^{119} r_{t-j}\right)^2. \tag{7}$$

This method recognizes the fact that data from the distant past may not be helpful for predicting future variance as the market condition changes.

Over the out-of-sample period, an investor using a model j to forecast returns will earn an average utility level of

$$\hat{v}_j = \hat{\mu}_j - \left(\frac{1}{2}\right)\gamma\hat{\sigma}^2_j, \tag{8}$$

where $\hat{\mu}_j$ and $\hat{\sigma}^2_j$ are the sample mean and variance of returns of the portfolio formed by the excess return forecasts based on the historical average (h) and the predictive model (p), respectively. $\hat{v}_p - \hat{v}_h$ is the difference in the certainty equivalent returns for the two different portfolio choices, which gives a direct measure of economic significance based on utility gains.[13]

3. Data

The data are from five 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 combine data of individual bonds from these sources to construct a large sample for empirical tests. Using individual bond data allows us to have better control on the effects of duration, provisions, and other bond characteristics in empirical tests, which is not possible when using bond yield indices (e.g., Barclays or formerly Lehman Brothers indices).

The LBFI database contains monthly data on corporate and government debt issues in the United States from January 1973 to March 1998. Data items include month-end prices, accrued interest, rating, amount outstanding, issue date, maturity date, provisions, and other bond characteristics. We exclude matrix prices and include all U.S. corporate fixed-coupon bonds that are not backed by mortgages or other assets.

Daily prices for corporate bonds, available from 1990, are obtained from Datastream, which uses Merrill Lynch as the data source. Datastream covers the bonds included in the Lehman corporate bond indices. The price is an average across all market makers for the bond. We construct monthly bond returns from month-end price observations. We exclude non-U.S.-dollar-denominated bonds and bonds with unusual coupons or backed by mortgages or other assets.

[12] The risk aversion coefficient is set equal to three as in Campbell and Thompson (2008).

[13] Following Campbell and Thompson (2008), we constrain the portfolio weights within a range of 0–300%.

The NAIC and TRACE databases contain transaction data of corporate bonds. Data from NAIC consist of all transactions of corporate bonds by life, property, and casualty insurance companies and health maintenance organizations beginning from January 1994. The TRACE database covers transactions of publicly traded corporate bonds starting from July 2002. We collect the data up to December 2010 and use bond characteristic information in the FISD to identify and eliminate non-U.S.-dollar-denominated bonds and bonds backed by mortgages or other assets. We follow the data screening procedure in Bessembinder et al. (2009) to eliminate cancelled, corrected, and commission trades. To obtain monthly returns for TRACE and NAIC, we first compute daily prices as the trade size-weighted average of intraday prices over the day as in Bessembinder et al. (2009) and then use the month-end price to calculate returns. The monthly corporate bond return as of time t is computed as follows:

$$R_t = \frac{(P_t + A_t) + C_t - (P_{t-1} + A_{t-1})}{P_{t-1} + A_{t-1}}, \tag{9}$$

where P_t is the price, A_t is accrued interest, and C_t is the coupon payment, if any, in month t.

Monthly returns calculated from the TRACE and NAIC databases are merged and screened to eliminate duplicate return records for the same bond in each month. These return data are further combined with those obtained from LBFI and Datastream. We keep only one return record if the same bond is covered in more than one database in any period to avoid overlapping data. We drop the Datastream data if returns are available from other sources.[14] When both LBFI data and transaction-based data are available, we choose transaction-based return data.

The FISD database includes issuance information for all fixed-income securities that have a CUSIP or are likely to receive one soon. It contains issue- and issuer-specific information, such as coupon rate, issue date, maturity date, issue amount, rating, and other bond characteristics for bonds maturing in 1990 or later.

To avoid confounding effects, we focus on straight bonds in empirical tests. Bonds with embedded options are excluded and so are bonds with less than one year maturity and longer than 30 years. Our final sample includes 846,857 bond-month observations from January 1973 to December 2010, with 27,190 bonds issued by 3,182 firms. Among them, 272,918 bond-month observations are extracted from TRACE, 291,484 from LBFI, 126,518 from NAIC, and 155,937 from Datastream.[15]

In Panel A of Table 1 we summarize the distribution of corporate bond data in percentages. The data sample is fairly evenly spread across maturities and ratings. A-rated bonds have the largest proportion, accounting for 39% of the sample. The speculative-grade bonds account for a little over 10% of the sample, with about 87,560 bond-month observations. The size of the speculative-grade bond subsample is sufficiently large for in-depth analysis. Across maturities, long-term bonds (with maturity greater than 10 years and less than 30 years) take up a sizable proportion (21.56%). Among the four data sources, LBFI contributes the most to the data sample (34.42%), followed by TRACE (32.23%), Datastream (18.41%), and NAIC (14.94%). The variation in the data share is partly due to differences in the coverage of bonds by each database over time.

We form bond portfolios by rating and duration. We use duration as an effective maturity measure by taking account of coupon structure. Using the duration calculated from individual bond data permits better control for the maturity of portfolios. To construct monthly returns of portfolios, we first calculate mean returns of individual bonds each month. For each bond, we calculate the return in excess of a duration-matched Treasury bond portfolio return. We sort all bonds independently into five rating portfolios and five duration portfolios in each month. In all, 25 duration portfolios are formed at the intersection of the rating and duration. We calculate both equal- and value-weighted portfolio returns each month, but we focus on the results of value-weighted portfolio returns where the weight is based on the market value of each bond at the beginning of each month.

[14] Datastream data are perceived to be of lower quality than those from other sources.

[15] There are missing data in August 1975 and December 1984 in the LBFI database.

Table 1
Summary statistics.

Panel A reports the percentage distribution of the corporate bond data sample by rating and maturity and the sources of data. The sample includes 27,190 bonds issued by 3,182 firms from January 1973 to December 2010. Panel B reports summary statistics of rating and duration portfolios. In each month, we sort all bonds independently into five rating portfolios and five duration portfolios (1 is short- and 5 is long-duration). In all, 25 duration portfolios are constructed at the intersection of rating and duration (DT).

Panel A: Sample distribution

Maturity	AAA	AA	A	BBB	BB	B	CCC	Below CCC	All
				Distribution by maturity (%)					
2	1.68	3.05	5.56	2.16	0.86	0.36	0.08	0.20	13.94
3	1.35	2.89	5.11	2.08	0.74	0.29	0.05	0.13	12.65
4	1.00	2.39	4.29	1.91	0.55	0.24	0.05	0.11	10.55
5	0.99	2.26	4.02	1.85	0.54	0.20	0.06	0.10	10.02
6	0.60	1.40	2.74	1.51	0.43	0.20	0.06	0.07	7.01
7	0.63	1.27	2.72	1.58	0.42	0.21	0.05	0.07	6.96
8	0.57	1.02	2.28	1.35	0.33	0.17	0.04	0.06	5.82
9	0.53	0.99	2.32	1.44	0.32	0.13	0.03	0.04	5.80
10	0.49	0.91	2.25	1.53	0.32	0.12	0.03	0.03	5.69
>10	1.38	2.86	7.72	6.95	1.40	0.70	0.35	0.19	21.56
All	9.22	19.06	39.03	22.36	5.92	2.63	0.81	0.98	100.00
				Distribution by data source (%)					
Datastream	1.13	3.44	5.15	6.10	1.28	0.89	0.40	0.01	18.41
LBFI	2.10	5.73	15.16	8.39	1.61	0.65	0.05	0.73	34.42
NAIC	3.86	1.97	5.08	2.93	0.76	0.26	0.07	0.02	14.94
TRACE	2.14	7.92	13.63	4.94	2.27	0.82	0.29	0.22	32.23
All	9.22	19.06	39.03	22.36	5.92	2.63	0.81	0.98	100.00

Panel B: Summary statistics

(1) By rating

Rating	Excess returns (%)	Std. (%)	Corr. with equity returns	Excess returns (%)	Std. (%)	Corr. with equity returns
		Equal-weighted			Value-weighted	
AAA	0.04	1.63	0.25	0.06	1.54	0.23
AA	0.09	1.58	0.32	0.09	1.48	0.31
A	0.10	1.69	0.34	0.12	1.65	0.34
BBB	0.16	1.88	0.36	0.19	1.71	0.39
Junk	0.28	1.92	0.44	0.37	1.99	0.47

(2) By duration

	Equal-weighted Portfolio		Value-weighted Portfolio		Equal-weighted Portfolio		Value-weighted Portfolio	
DT	Excess returns (%)	Std. (%)	Excess returns (%)	Std. (%)	Excess returns (%)	Std. (%)	Excess returns (%)	Std. (%)
		AAA				AA		
1	0.06	0.76	0.06	0.77	0.10	0.74	0.09	0.76
2	0.04	1.23	0.04	1.27	0.09	1.32	0.08	1.34
3	0.06	1.76	0.05	1.76	0.09	1.73	0.07	1.75
4	0.04	2.15	0.05	2.26	0.08	2.08	0.09	2.04
5	0.07	2.50	0.06	2.56	0.09	2.41	0.09	2.42
		A				BBB		
1	0.11	0.84	0.12	0.90	0.18	1.26	0.19	1.17
2	0.11	1.42	0.10	1.50	0.15	1.84	0.18	1.83
3	0.08	1.83	0.08	1.88	0.12	2.25	0.14	2.14
4	0.07	2.25	0.10	2.30	0.07	2.49	0.13	2.46
5	0.11	2.50	0.13	2.52	0.23	2.52	0.18	2.47

Table 1 (*continued*)

(2) By duration

DT	Equal-weighted Portfolio Excess returns (%)	Equal-weighted Portfolio Std. (%)	Value-weighted Portfolio Excess returns (%)	Value-weighted Portfolio Std. (%)	Equal-weighted Portfolio Excess returns (%)	Equal-weighted Portfolio Std. (%)	Value-weighted Portfolio Excess returns (%)	Value-weighted Portfolio Std. (%)
		Junk						
1	0.20	2.04	0.25	2.27				
2	0.20	2.11	0.29	2.25				
3	0.22	2.23	0.25	2.35				
4	0.30	2.36	0.36	2.52				
5	0.55	2.99	0.66	3.12				

Panel B of Table 1 reports summary statistics for rating and duration portfolios. Both mean and standard deviation of excess returns increase as the rating decreases. The correlation between bond and stock excess returns is higher for bonds with lower ratings. Summary statistics for duration portfolios are reported by rating category. Portfolio 1 has the shortest duration and portfolio 5 has the longest duration. Portfolios with long duration have high mean returns and standard deviations.

Major forecasting variables include dividend yields, term spreads, default spreads, the CP forward rate factor, liquidity factors, and the bond portfolio's credit spread. Dividend yields are extracted from the equity returns that includes and excludes dividends where return data are from the CRSP. Dividend yields exhibit a time trend, and so we use the detrended D/P ratio as an explanatory variable in regressions. The term spread is the difference between 10- and 1-year Treasury bond yields and the default spread is the difference between average yields of AAA and BBB bonds. The portfolio's credit spread is the individual bond's credit spread, the yield minus the duration-matched Treasury bond rate, averaged across bonds in a rating and duration portfolio.

The original CP factor is a single linear combination of forward rates, which can be constructed from the parameters of the following regression:

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1 y_t^{(1)} + \gamma_2 f_t^{(2)} + \cdots + \gamma_5 f_t^{(5)} + \overline{\varepsilon}_{t+1}, \tag{10}$$

or in the vector notation,

$$\overline{rx}_{t+1} = \boldsymbol{\gamma}^T \mathbf{f}_t + \overline{\varepsilon}_{t+1}, \tag{11}$$

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 γ coefficients are used to construct the CP factor $\hat{\boldsymbol{\gamma}}^T \mathbf{f}_t$ for forecasting bond returns. To match our sample period, we use the Fama-Bliss data of one- through five-year zero-coupon bond prices (available from CRSP) from 1973 to 2010 to estimate forward rates and $\hat{\boldsymbol{\gamma}}$, and then obtain the linear combination $\hat{\boldsymbol{\gamma}}^T \mathbf{f}_t$ as the CP factor.[16]

We refer to the factor estimated from (10) as the CP five-year factor. Besides this factor, we construct another CP factor associated with maturity, $n=10$, to capture the information for long-term interest rate expectations. Because expectations of long-term interest rates affect prices of long-term bonds, including more distant forward rates ($n>5$) can be helpful for forecasting returns of long-term corporate bonds. The CP factor with $n=10$ can be obtained by extending the formula in (10) to 10-year maturity. Specifically, we run a regression of average excess log returns of Treasury bonds on all

[16] The coefficient estimates are $\hat{\gamma}_0 = -1.18$, $\hat{\gamma}_1 = -1.40$, $\hat{\gamma}_2 = -0.47$, $\hat{\gamma}_3 = 2.98$, $\hat{\gamma}_4 = 0.84$, and $\hat{\gamma}_5 = -1.75$, and the adjusted R^2 is 24%.

forward rates at time t up to $n=10$:

$$\frac{1}{9}\sum_{n=2}^{10} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1 y_t^{(1)} + \gamma_2 f_t^{(2)} + \cdots + \gamma_5 f_t^{(5)} + \gamma_6 f_t^{(6)} + \cdots + \gamma_{10} f_t^{(10)} + \overline{\varepsilon}_{t+1}. \tag{12}$$

We refer to the forward rate factor constructed from this regression as the CP 10-year factor. In empirical investigation, we employ both the CP five- and ten-year factors and compare their predictive ability for bonds with different maturities. To estimate the regression model in (12), we collect yield data from the Federal Reserve Bank (FRB) for Treasury securities with constant maturities of 6-month, 1-, 2-, 3-, 5-, 7-, and 10-years to estimate spot and forward rates.[17]

We account for the estimation uncertainty embedded in the coefficients in (10) and (12) when running the predictive regression with the CP factors. We use the method in Murphy and Topel (1985) to adjust for the impacts of parameter estimation uncertainty stemming from the generated regressor on standard errors and R^2. In addition, when conducting the out-of-sample test, we construct the CP factors in real time by estimating the linear combination of forward rates with data up to the time the forecast is made.

Næs, Skjeltorp, and Odegaard (2011) find a strong relation between stock market liquidity and the current and future state of the economy. As asset risk premiums are related to changing business conditions, we incorporate the liquidity factor in the model to see if it has predictive power. Using aggregate liquidity measures, we examine whether variations in corporate bond risk premiums are related to changes in market liquidity conditions. Liquidity has many dimensions and we consider various measures for market-wide liquidity. The long sample period and data availability, however, constrain our choice of liquidity variables. We select on-/off-the-run spreads, changes in money market mutual fund assets, and Hasbrouck's effective trading cost index (Hasbrouck, 2009) as base measures of market liquidity.[18]

The on-/off-the-run spread is taken from the difference between the five-year constant-maturity Treasury rate from the FRB and the five-year generic Treasury rate reported by Bloomberg (see Pflueger and Viceira, 2011).[19] The on-/off-the-run spread has been shown to reflect future liquidity conditions (see Goldreich, Hanke, and Nath, 2005). A large spread signals that the market liquidity condition will worsen (Longstaff, Mithal, and Neis, 2005). Money market mutual funds represent a hedge against flight to quality or liquidity. Longstaff, Mithal, and Neis (2005) show that large inflows into these funds reflect market illiquidity. We calculate monthly percentage changes in total money market mutual fund assets ($\Delta MMMF$) using the data from the FRB. Both on-/off-the-run spreads and $\Delta MMMF$ are available for the whole sample period. The Hasbrouck trading cost index, which runs from 1926 to 2005, was downloaded from Hasbrouck's website. This index measures illiquidity from the perspective of trading cost. We use the data for the period 1973–2005 in our tests.

The corporate bond return may be predictable because it is correlated with the stock market return. Elton et al. (2001) show that corporate bond returns have positive betas. Thus, factors that predict the stock market return may also have predictive power for the corporate bond return. To examine this possibility, we also consider equity market variables, such as earnings yields, return volatility, and growth rates, as predictors. Campbell and Thompson (2008) and Welch and Goyal (2008) show that these variables have predictive power for stock market returns. We consider these variables in the model to see if they have additional predictive power over and beyond the bond market and liquidity variables.

[17] Since the FRB six-month constant yield to maturity data series start only from 1982, we use the six-month Treasury bill rate before 1982. Also, as the two-year constant yield-to-maturity data are available only from 1976, we use the interpolation of one- and three-year yields from 1973 to 1976. We then utilize a standard cubic spline algorithm to interpolate these par yields at semi-annual intervals and bootstrap them to provide a discount rate curve. The cubic spline function is $y=a_0+a_1x+a_2x^2+a_3x^3$.

[18] We also consider Pastor-Stambaugh's (2003) and Amihud's (2002) stock and bond liquidity measures. However, we find these variables do not perform better than other liquidity measures.

[19] Longstaff, Mithal, and Neis (2005) use similar data to obtain on-/off-the-run spreads.

Table 2
In-sample results of univariate predictive regressions.

This table reports the results of univariate predictive regressions for rating portfolios. The predictors include dividend–price ratio (*D/P*), earnings–price ratio (*E/P*), stock return variance (*Var*), growth ratio (*Growth*), term spread (*TMS*), default spread (*DFS*), CP five-year factor (*CP5*), CP ten-year factor (*CP10*), on-/off-the-run spread (*Onoff*), percentage changes in the money market mutual fund flow (Δ*MMMF*), effective cost (*EC*), the bond portfolio's credit spread (*CSP*), and the Dick-Nielsen, Feldhutter, and Lando (2012) liquidity measure (DFL). Standard errors are adjusted by the Hodrick (1992) method to account for the impact of overlapping residuals and by the method of Murphy and Topel (1985) to account for the impact of two-step regressions when the CP factor is used as a predictor. Diff is the difference between speculative-grade and AAA portfolios. The *t*-value of Diff is calculated from the standard error based on the method of Ang and Bekaert (2007). The time period using *DFL* is from 1994 to 2010.

		Monthly						Quarterly						Yearly					
	Variable	AAA	AA	A	BBB	Junk	Diff	AAA	AA	A	BBB	Junk	Diff	AAA	AA	A	BBB	Junk	Diff
	D/P	0.22	0.27	0.39	0.44	0.59	0.37	0.19	0.24	0.35	0.43	0.51	0.32	0.10	0.16	0.24	0.37	0.40	0.30
	E/P	−0.06	−0.30	−0.28	−0.41	−0.58	−0.52	−0.07	−0.29	−0.27	−0.38	−0.49	−0.42	−0.07	−0.25	−0.23	−0.35	−0.48	−0.41
	Var	0.49	0.71	0.82	0.76	0.70	0.21	0.42	0.72	0.74	0.85	0.88	0.46	0.10	0.43	0.53	0.77	1.04	0.94
	Growth	−0.17	−2.42	−3.67	−5.08	−7.46	−7.29	0.15	−2.11	−3.59	−4.95	−6.81	−6.96	0.57	−1.55	−3.13	−4.73	−7.11	−7.68
Coefficient	*TMS*	0.17	0.24	0.30	0.40	0.40	0.23	0.15	0.21	0.26	0.35	0.35	0.20	0.13	0.18	0.23	0.30	0.33	0.20
	DFS	0.16	0.31	0.45	0.55	0.59	0.43	0.09	0.25	0.41	0.52	0.48	0.39	0.11	0.27	0.41	0.56	0.62	0.51
	CP5	0.07	0.07	0.09	0.10	0.08	0.01	0.10	0.10	0.12	0.12	0.11	0.01	0.11	0.10	0.12	0.12	0.11	0.00
	CP10	0.05	0.05	0.05	0.05	0.05	0.00	0.06	0.06	0.06	0.05	0.05	−0.01	0.06	0.06	0.06	0.06	0.06	0.00
	Onoff	1.58	1.53	1.62	1.82	2.28	0.70	0.51	0.59	0.63	0.75	0.96	0.45	0.31	0.35	0.36	0.44	0.49	0.18
	Δ*MMMF*	0.03	0.03	0.05	0.05	0.05	0.02	0.02	0.03	0.04	0.04	0.05	0.03	0.01	0.02	0.02	0.02	0.03	0.02
	EC	0.39	0.50	0.58	0.57	0.83	0.44	0.12	0.24	0.33	0.37	0.64	0.52	0.00	0.05	0.08	0.13	0.23	0.23
	CSP	−0.03	0.18	0.24	0.26	0.17	0.20	0.05	0.24	0.26	0.27	0.16	0.11	0.09	0.23	0.29	0.29	0.20	0.11
	DFL	0.17	0.76	0.97	1.12	1.55	1.37	0.07	0.71	0.90	1.15	1.38	1.32	0.00	0.63	0.86	1.19	1.64	1.64
	D/P	1.77	2.40	3.09	3.27	3.77	1.89	1.75	2.29	2.70	3.00	2.65	1.67	1.09	1.78	2.27	3.00	2.54	1.93
	E/P	−0.48	−2.38	−2.06	−2.79	−3.42	−2.33	−0.46	−2.02	−1.57	−2.04	−2.07	−1.99	−0.55	−1.96	−1.57	−2.24	−2.56	−2.58
	Var	2.07	3.22	3.37	2.91	2.28	1.06	7.24	9.36	6.62	6.77	5.04	2.78	2.57	8.87	7.41	8.97	8.73	7.80
	Growth	−0.10	−1.57	−2.17	−2.80	−3.55	−2.66	0.12	−1.64	−2.08	−2.51	−2.54	−2.64	0.51	−1.49	−2.56	−3.33	−3.76	−4.04
	TMS	2.20	3.41	3.82	4.81	4.04	2.84	1.70	2.57	3.08	3.77	3.33	2.70	1.61	2.23	2.76	3.39	3.29	2.93
t-stats	*DFS*	1.13	2.32	3.07	3.52	3.19	1.60	0.61	1.61	2.04	2.39	1.76	1.54	0.84	2.11	2.80	3.45	3.10	2.82
	CP5	1.66	1.70	1.89	1.87	1.40	0.07	2.04	2.02	2.17	2.04	1.84	0.42	2.46	2.34	2.45	2.29	2.04	0.06
	CP10	3.03	3.24	2.97	2.85	2.11	0.35	2.73	2.65	2.58	2.27	1.95	0.29	3.01	2.93	3.00	2.68	2.55	0.14
	Onoff	5.23	5.42	5.23	5.45	5.91	2.57	2.51	3.20	3.30	4.03	4.29	2.44	2.79	3.48	3.36	3.91	4.05	1.82
	Δ*MMMF*	1.62	2.33	2.82	3.08	2.50	3.16	1.25	1.81	2.48	2.72	2.64	3.58	0.69	1.36	1.28	1.69	2.18	3.67
	EC	1.41	2.00	2.19	2.05	2.78	1.75	0.62	1.40	1.72	1.98	2.81	2.79	0.04	0.47	0.72	1.17	1.89	2.09
	CSP	−0.24	1.74	2.98	4.19	4.83	1.89	0.30	2.03	2.06	2.58	2.20	1.67	0.65	2.99	3.10	3.94	3.69	1.93
	DFL	0.71	2.37	1.96	1.88	1.84	1.76	0.36	2.53	1.95	2.19	1.93	1.89	0.00	4.17	3.51	3.96	3.74	3.60

	D/P	0.71	1.29	2.12	2.37	3.14	1.31	2.31	3.60	4.82	5.27	1.39	3.54	6.02	10.82	8.86
	E/P	0.05	1.27	0.96	1.74	2.58	0.13	2.74	1.82	3.14	4.14	0.64	7.20	4.41	8.20	10.41
	Var	0.96	2.30	2.52	1.89	1.17	1.67	5.30	4.32	4.93	4.19	0.34	6.60	7.65	12.47	15.43
	Growth	0.00	0.56	1.06	1.75	2.79	0.00	0.97	2.12	3.55	5.26	0.25	1.82	5.60	10.02	15.13
	TMS	1.09	2.57	3.22	5.00	3.58	1.88	4.49	5.16	7.89	6.32	6.23	11.17	13.85	18.27	14.62
R^2 (%)	*DFS*	0.29	1.21	2.10	2.74	2.26	0.23	1.80	3.66	5.08	3.46	1.29	7.00	12.87	18.39	15.09
	CP5	0.84	0.90	1.23	1.19	0.55	3.49	3.98	4.28	3.74	2.75	17.82	15.30	16.79	11.85	7.28
	CP10	2.42	2.83	2.32	2.11	1.09	7.32	7.20	5.99	4.55	3.52	30.32	27.40	24.40	17.02	12.77
	Onoff	5.85	6.26	5.85	6.33	7.35	1.44	2.12	1.83	2.30	2.93	2.08	2.60	2.03	2.41	2.06
	Δ*MMMF*	0.61	1.24	1.83	2.16	1.44	0.82	1.90	2.68	2.89	2.54	0.67	2.59	2.03	2.95	3.56
	EC	0.51	1.01	1.20	1.06	1.94	0.11	0.55	0.85	0.97	2.46	0.00	0.08	0.18	0.41	1.12
	CSP	0.01	0.69	2.00	3.87	5.07	0.08	2.84	4.99	9.30	10.60	0.97	9.06	20.21	31.80	40.92
	DFL	0.24	5.54	6.63	6.09	6.97	0.10	10.71	11.30	14.55	13.25	0.00	31.91	36.90	45.68	42.21

4. The regressions

4.1. Univariate regressions

We first run univariate regressions of excess returns against each predictor. The dependent variable is value-weighted excess returns for each rating portfolio. Table 2 reports results of regressions for monthly, quarterly, and yearly return horizons. Consistent with the finding of Fama and French (1989), the results show that dividend yields, term spreads, and default spreads have in-sample predictive power. More importantly, we find that the CP and liquidity factors, the bond portfolio's credit spread, and equity variables also have in-sample predictive power. Slope coefficients of all predictors in absolute terms increase as the rating decreases, reflecting the variation in expected corporate bond returns that increase with default risk.

The CP factors tend to have higher predictive power in terms of t and R^2 for higher-grade bonds than for lower-grade bonds. The CP ten-year factor performs better than the CP five-year factor, suggesting that the former contains more information. By contrast, the portfolio's credit spread (*CSP*) has higher predictive power for lower-grade bonds. The *CSP* has predictive power for all bonds except AAA. This is likely because default risk is not an important concern for top-quality bonds. Equity variables have predictive power for lower-grade bonds. Lower-grade bonds behave more like stocks (see Kwan, 1996) and their returns are more correlated with stock returns (Table 1). For liquidity variables, the on-/off-the-run spread appears to have higher predictive power than money market fund flow ($\Delta MMMF$) and the Hasbrouck effective trading cost (*EC*) index.

In the analysis above, we use conventional liquidity measures to capture the effect of liquidity. Recently, Dick-Nielsen, Feldhutter, and Lando (2012) propose a new liquidity index as a liquidity factor for the corporate bond market. They find that this index is a better liquidity measure than other indices. To investigate whether this liquidity index has predictive power for corporate bond returns, we further employ this index for in- and out-of-sample forecasts.

The Dick-Nielsen-Feldhutter-Lando (hereafter DFL) liquidity index is a factor that loads evenly on four individual liquidity measures: the Amihud illiquidity measure, the imputed roundtrip cost (IRC), the Amihud risk, and the IRC risk. The IRC is set equal to $(P_{max}-P_{min})/P_{max}$, where P_{max} is the largest price in the imputed roundtrip trades and P_{min} is the smallest price (see Feldhutter, 2012), and the daily round trip cost is the average of roundtrip costs on that day for different trade sizes. The Amihud and IRC measures are mean daily Amihud and IRC measures, while the Amihud risk and IRC risk are standard deviations of daily Amihud and IRC measures.

We construct the liquidity index using the method of Dick-Nielsen, Feldhutter, and Lando (2012). For each bond i in month t, we first calculate I^j_{it}, where $j=1, 2, 3, 4$ is an indicator for the Amihud, IRC, Amihud risk, and IRC risk measures, respectively. We then standardize each individual measure by $\tilde{I}^j_{it}=(I^j_{it}-m^j)/\sigma^j$, where m^j and σ^j are the mean and standard deviation of I^j across bonds and months in each period. The measures are calculated based on the bond transaction data, which are available after 1994. We divide the 1994–2010 sample period into three sub periods (January 1994 to June 2002, July 2002 to September 2004, and October 2004 to December 2010) to account for the effects of structure breaks induced by three different phases of TRACE coverage for bond transactions and calculate the standardized liquidity measures using mean and standard deviation for each period separately.[20] The individual liquidity measure λ_{it} for each bond and each month is defined as $\lambda_{it}=\Sigma^4_{j=1}\tilde{I}^j_{it}$. The monthly aggregate liquidity index is constructed by taking the mean of λ_{it} in each month across bonds. We calculate the DFL liquidity measure λ_{it} based on both the monthly and quarterly horizon and find that the monthly measure performs slightly better than the quarterly measure in the predictive regression for our data sample. We therefore choose the monthly DFL liquidity index in our empirical tests.

[20] The TRACE was introduced in July 2002. Initially, it covered only a subset of publicly traded bonds. On October 1, 2004, the TRACE database was expanded further to cover all publicly traded corporate bonds. These changes corresponding to different phases of TRACE expansions induce shifts in the time series of our corporate bond data. We find that accounting for these shifts produces more stable liquidity measures.

Table 3
Slopes, t-statistics, and adjusted R^2 from multiple regressions.

This table reports in-sample results of multiple predictive regressions for the one-year horizon. The dependent variable is the duration-adjusted portfolio yearly excess return. In the first panel, predictors include term and default spreads. In the second panel, predictors include the CP ten-year factor (*CP10*), term spread (*TMS*), dividend–price ratio (*D/P*), default spread (*DFS*), on-/off-the-run spread (*Onoff*), changes in the money market mutual fund flow (Δ*MMMF*), effective cost (*EC*), and the bond portfolio's credit spread (*CSP*). In the third panel, earnings–price ratio (*E/P*), stock return variance (*Var*) and growth ratio (*Growth*) are used as the predictors. In the last panel, the CP ten-year factor (*CP10*), term spread (*TMS*), default spread (*DFS*), on-/off-the-run spread (*Onoff*), stock return variance (*Var*), growth ratio (*Growth*), and the portfolio's credit spread (*CSP*) are used as the predictors. Standard errors are adjusted by the Hodrick (1992) method to account for the impact of overlapping residuals and by the Murphy-Topel (1985) method for the impact of two-step regressions when the CP factor is used as a predictor. The t-values are in parentheses.

	CP10	*TMS*	*D/P*	*DFS*	*Onoff*	Δ*MMMF*	*EC*	*EP*	*Var*	*Growth*	*CSP*	Adj. R^2
$r_{t+1}=\alpha+\beta_1 TMS_t+\beta_2 DFS_t+\varepsilon_{t+1}$												
AAA		0.13		0.08								6.47
		(1.47)		(0.58)								
AA		0.16		0.22								15.74
		(1.95)		(1.73)								
A		0.20		0.36								23.26
		(2.39)		(2.42)								
BBB		0.26		0.49								32.09
		(2.95)		(3.1)								
Junk		0.29		0.55								25.93
		(2.88)		(2.79)								
$r_{t+1}=\alpha+\beta_1 CP10_t+\beta_2 TMS_t+\beta_3 D/P_t+\beta_4 DFS_t+\beta_5 Onoff_t+\beta_6 \Delta MMMF_t+\beta_7 EC_t+\beta_8 CSP_t+\varepsilon_{t+1}$												
AAA	0.09	−0.11	−0.04	0.00	0.14	−0.01	0.08				0.01	36.96
	(3.17)	(−0.91)	(−0.2)	(0.00)	(0.93)	(−1.12)	(0.54)				(0.05)	
AA	0.08	−0.12	−0.03	−0.01	0.25	−0.01	0.10				0.10	40.45
	(3.09)	(−0.99)	(−0.17)	(−0.04)	(1.59)	(−0.51)	(0.75)				(0.48)	
A	0.08	−0.12	0.05	0.01	0.30	0.00	0.01				0.27	43.13
	(3.48)	(−1.09)	(0.29)	(0.05)	(2.57)	(−0.11)	(0.07)				(1.74)	
BBB	0.07	−0.03	0.01	0.01	0.33	0.00	0.04				0.22	40.47
	(2.72)	(−0.29)	(0.08)	(0.03)	(2.69)	(−0.15)	(0.37)				(1.90)	
Junk	0.07	−0.15	0.10	0.06	0.36	0.00	0.14				0.19	51.42
	(2.75)	(−1.18)	(0.46)	(0.24)	(3.49)	(−0.30)	(1.04)				(3.56)	
$r_{t+1}=\alpha+\beta_1 E/P_t+\beta_2 Var_t+\beta_3 Growth_t+\varepsilon_{t+1}$												
AAA								−0.06	0.09	0.76		0.50
								(−0.46)	(2.24)	(0.64)		
AA								−0.19	0.28	−0.95		10.45
								(−1.5)	(6.75)	(−0.92)		
A								−0.15	0.37	−2.44		11.88
								(−1.04)	(6.5)	(−2.08)		
BBB								−0.23	0.51	−3.74		21.17
								(−1.58)	(8.23)	(−2.85)		
Junk								−0.33	0.66	−5.80		28.76
								(−1.87)	(8.37)	(−3.41)		
$r_{t+1}=\alpha+\beta_1 CP10_t+\beta_2 TMS_t+\beta_3 DFS_t+\beta_4 Onoff_t+\beta_5 Var_t+\beta_6 Growth_t+\beta_7 CSP_t+\varepsilon_{t+1}$												
AAA	0.07	−0.05		0.17	0.09				0.20	2.46	0.04	35.38
	(2.84)	(−0.39)		(0.87)	(0.66)				(3.37)	(1.10)	(0.21)	
AA	0.07	−0.05		0.13	0.24				0.19	1.67	0.24	43.53
	(2.68)	(−0.36)		(0.57)	(1.87)				(3.50)	(0.74)	(1.82)	
A	0.07	−0.05		0.16	0.26				−0.06	1.78	0.33	49.50
	(2.66)	(−0.38)		(0.67)	(1.88)				(−0.95)	(0.78)	(2.07)	
BBB	0.06	0.03		0.12	0.29				−0.00	1.92	0.3	53.59
	(2.46)	(0.24)		(0.51)	(2.26)				(−0.02)	(0.82)	(2.57)	
Junk	0.08	−0.14		0.14	0.21				0.07	−2.00	0.18	55.67
	(2.65)	(−1.00)		(0.59)	(1.63)				(0.99)	(−0.72)	(2.56)	

We examine the predictive power of the DFL liquidity index. The in-sample regression results are reported at the bottom of each panel in Table 2. Results show that the DFL liquidity index has predictive power in sample. The coefficients are all positive and significant for all bond ratings except AAA. The coefficients are most significant at the annual horizon, suggesting that the DFL liquidity has longer-term predictive power than most conventional liquidity indices.

4.2. Multiple regressions

Table 3 reports results of multiple regressions for value-weighted portfolio returns by rating. For brevity, we focus on results at the one-year return horizon.[21] The multiple regression allows us to see which variables have more predictive power in a horse race. We use only the CP ten-year factor in the regression as it has greater predictive power than the CP five-year factor. The first panel reports results based on only term and default spreads similar to Fama and French (1989). Results confirm that both variables have predictive power, which tends to increase as the rating decreases. The second panel reports results of multiple regressions that include dividend yields, the CP factor, liquidity variables, and the portfolio's credit spread as predictors. Results show that the CP ten-year factor is highly significant across ratings. The on-/off-the-run spread is more significant than $\Delta MMMF$ and the effective cost index (EC). The portfolio's credit spread (CSP) is more significant for lower-grade bonds. By contrast, dividend yields, term spreads, and default spreads become insignificant.[22] The adjusted R^2 increases substantially when we include additional predictors and it increases as the rating decreases. The results indicate that lower-grade bond returns are more predictable.

The third panel in Table 3 reports results that use equity variables as predictors. The results show that stock market return volatility (Var) has in-sample predictive power for all bonds. The growth rate variable also has predictive power, which is higher for lower-grade bonds. However, earnings yields become insignificant after we include all variables. We also consider other equity variables such as book-to-market ratio and inflation. These variables have been shown to have predictive power for stock returns (Fama and Schwert, 1977; Guo, 2006; Campbell and Thompson, 2008; Ferreira and Santa-Clara, 2011). However, the results (omitted for brevity) show that none of these variables is significant in multiple regressions.

The last panel in Table 3 reports the results of regressions that include seven key predictors from both bond and stock markets. We exclude $\Delta MMMF$, EC, D/P, and E/P as they appear to be dominated by other predictors. The results show that the CP ten-year factor, on-/off-the-run spreads, the portfolio's credit spread, and stock market return volatility have higher in-sample predictive power than other predictors. The adjusted R^2 ranges from 35% for AAA bonds to 56% for speculative-grade bonds. Adding the equity variables does not improve the predictive power for AAA bond returns. This finding is consistent with the traditional view that high-grade bonds behave more like Treasury bonds. Overall, there is strong evidence that corporate bond returns are predictable in sample and speculative-grade bond returns are more predictable than high-grade bonds.

5. Out-of-sample forecasts

5.1. Out-of-sample individual forecasts

The above results for in-sample regressions show that variables related to business conditions and term structure can predict corporate bond returns. However, this finding does not guarantee good out-of-sample performance for these variables. Welch and Goyal (2008) find that a number of "good" predictors from the literature have worse out-of-sample forecasts of the equity premium than

[21] Most studies of return predictability focus on the predictability of one-year bond returns (e.g., Cochrane and Piazzesi, 2005).

[22] Collinearity may contribute to the insignificance of these variables.

Table 4
Out-of-sample forecast performance.

This table reports out-of-sample R^2_{OS} values (%) of individual and combination forecasts at monthly (M), quarterly (Q) and one-year (1) horizons. On the right panel, we report results for portfolios of long (5) and short (1) durations. The predictors include dividend–price ratio (*D/P*), earnings–price ratio (*E/P*), stock variance (*Var*), growth ratio (*Growth*), term spread (*TMS*), default spread (*DFS*), CP five-year factor (*CP5*), CP ten-year factor (*CP10*), on-/off-the-run spread (*Onoff*), percentage changes in money market mutual fund flow (Δ*MMMF*), effective cost (*EC*), the bond portfolio's credit spread (*CSP*), and the Dick-Nielsen, Feldhutter, and Lando (2012) liquidity measure (DFL). For combination forecasts, we report mean and median forecasts. 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 Hodrick (1992) method to account for the impact of overlapping residuals when the forecast horizon is quarterly and annual. ***, **, * Indicate significance at the 1%, 5%, and 10% level, respectively.

		Rating portfolios					Duration portfolios									
		AAA	AA	A	BBB	Junk	AAA		AA		A		BBB		Junk	
							1	5	1	5	1	5	1	5	1	5
D/P	M	0.45*	1.82***	1.35**	1.39**	1.71**	−1.65	0.70	0.03	2.01**	1.56**	1.72**	3.66**	0.93**	1.20**	1.61***
	Q	−0.33	1.93*	0.10	1.32*	0.94*	−3.07	1.12	−2.34	2.31*	−1.32	1.93*	2.87	3.93***	2.29*	2.05***
	1	0.65	2.58	−2.62	0.70	−1.30	0.21	5.81	−3.01	5.23	−3.95	3.30	6.42	1.49	2.81	3.52**
E/P	M	−7.91	−0.10	−1.23	0.77*	−1.28	−44.70	−1.92	−3.10	1.03**	−4.36	1.92**	−1.06	1.84***	−15.32	−1.02
	Q	−5.42	3.49**	2.48*	2.44***	1.01*	−5.23	4.16*	0.17*	4.61**	−9.58	3.33*	−8.97	7.50***	−31.20	−0.58
	1	14.29	9.38*	−2.53	−6.68	4.29	−9.84	16.29	−7.28	16.13	−9.18	10.20*	−22.28	−42.47	−1.23	−38.23
Var	M	−0.37	1.35***	2.14*	−0.94	−2.17	−4.41	0.59**	−0.17	1.45**	7.35***	0.78**	4.01	−0.40	−0.51	−1.14
	Q	−1.03	5.92***	4.08**	5.36**	0.44***	−12.11	3.28**	−1.13	6.92***	4.86**	4.43**	9.31*	7.94***	8.51***	−0.28
	1	3.12	9.22	5.62	8.47	5.27*	−5.38	8.98	2.57	11.42	6.11	6.94	13.04	7.61	11.51*	0.03
Growth	M	−0.37	0.51***	−0.14	0.78**	3.36***	1.02**	−1.50	2.84***	−0.72	4.58***	0.67**	4.07***	−1.76	1.99**	4.23***
	Q	0.24	0.90*	−1.07	1.20*	5.47**	2.54***	−0.98	2.68**	−0.64	6.64***	0.95	5.93*	−1.48	4.81*	6.69***
	1	−1.59	−0.77	−1.23	6.72	8.55	−1.12	−3.16	−6.62	−4.23	3.12	2.18	14.59	−35.43	11.63	8.48*
TMS	M	1.38**	3.34***	2.55***	2.33***	2.40***	2.71***	1.44**	3.55***	2.71***	3.91***	2.96***	2.26***	3.38***	0.65**	3.48***
	Q	3.03**	6.54***	4.76***	6.06***	5.10***	4.54**	4.29**	5.19**	5.32***	5.90**	5.85***	5.19**	10.07***	2.16	6.55***
	1	5.55*	14.56**	14.55**	18.87**	13.61***	4.83	14.16**	4.89	18.20***	8.90	21.84***	9.97	21.21***	5.77	8.88*
DFS	M	0.63*	1.62***	1.27	1.56	−0.71	−0.74	0.95*	0.27	0.91**	4.28**	0.68*	6.04**	0.50	1.08	−0.79
	Q	1.40*	3.06**	2.85	3.63	−1.40	−1.25	2.91**	−0.62	2.18**	6.60*	1.95*	7.88	3.77***	4.90	−0.59
	1	4.12*	9.77**	11.07*	15.46**	4.71	−3.61	8.38*	−1.23	11.03***	9.84	12.22***	19.51	5.95*	11.25	11.07***
CP5	M	1.09**	1.11**	0.73*	0.24	−1.56	1.43***	1.08**	0.89***	1.02**	0.05	0.87**	−0.64	0.91**	−0.54	−1.23
	Q	5.73***	4.62***	3.86***	2.13**	−2.18	9.83***	4.17***	5.20***	3.76***	2.66***	3.82***	0.14*	6.01***	−2.57	−1.54
	1	23.11***	15.88***	15.53***	7.39***	−3.59	28.31***	22.40***	12.50***	18.48***	8.95***	21.57***	−1.51	10.75***	−7.68	−12.51
CP10	M	4.01***	3.37***	2.80***	2.07***	0.12	6.76***	1.60**	3.83***	2.71***	2.45***	2.48***	0.55*	1.62***	−0.87	0.98**
	Q	11.81***	8.26***	7.58***	4.84***	0.80*	18.26***	6.21***	9.90***	6.38***	6.49***	7.17***	0.76*	7.07***	−3.23	2.49***
	1	25.40***	18.81***	17.76***	9.80***	−0.17	32.97***	20.69***	20.11***	18.79***	12.81***	22.63***	−2.61	11.35***	−9.71	−2.58
Onoff	M	4.02***	4.36***	3.10***	2.47***	3.84***	6.67***	2.14***	5.87***	2.85***	3.41***	2.89***	1.15***	2.67***	0.50**	1.02**
	Q	2.81	3.67	2.07	1.81	2.04	6.23*	3.13	5.14*	2.92	2.37	2.42	0.99	5.95**	0.37	0.84
	1	6.14	5.81	2.19	1.85	0.28	6.07	9.78	3.36	8.02	1.90	6.44	0.61	4.84	−1.13	−0.13
Δ*MMMF*	M	1.03**	1.83***	1.53**	1.30**	1.49***	1.03**	1.00*	1.82***	1.50**	1.87***	1.94***	0.60*	1.11**	0.11	1.85***
	Q	1.93*	3.29**	2.26*	2.46*	2.79**	1.78	2.71*	2.06*	3.02**	1.87	3.48**	0.63	5.48**	0.34	3.18***

Table 4 (*continued*)

		Rating portfolios					Duration portfolios									
		AAA	AA	A	BBB	Junk	AAA		AA		A		BBB		Junk	
							1	5	1	5	1	5	1	5	1	5
	1	5.34	8.44*	5.05	6.65	5.21*	2.45	10.46*	3.02	11.50**	1.92	11.13*	2.28	11.47	1.01	−0.03
EC	M	1.19**	2.26***	1.29**	0.21	−1.28	0.67**	1.34**	0.52**	2.29***	−0.18	1.49***	−0.62	0.63	1.29**	−2.52
	Q	1.64	2.64*	0.75	−0.32	−0.80	1.58	3.10**	−0.49	2.64*	−1.14	1.46	1.57*	3.51***	6.41**	−1.73
	1	4.36	4.63	1.31	−0.57	−2.58	3.93	9.04*	−0.10	9.10*	−4.26	9.01**	−3.47	8.02**	2.81	4.51
CSP	M	0.82**	1.41***	0.80	1.91	1.51**	1.73***	0.98*	1.79**	1.46***	12.63***	1.45***	11.26**	1.07*	0.71*	4.55***
	Q	1.17	4.47***	4.35**	9.21**	1.10***	10.13***	2.87**	7.59***	2.70**	22.36***	3.45***	22.29**	8.39***	10.97**	6.43**
	1	2.49	13.35***	23.51***	41.43***	38.67***	22.25***	9.82*	10.24***	12.52**	33.17**	10.34***	64.95**	19.42*	44.46*	15.79*
DFL	M	−2.12	6.17*	4.08	4.40	3.20*	5.75**	−4.30	18.95***	−1.32	24.59***	−2.25	11.47*	2.68	2.67	10.46***
	Q	−4.14	14.58	8.39	15.34*	9.35*	−2.02	−5.95***	35.04	1.73	37.97*	2.05	24.19	10.56**	21.69**	16.32**
	1	−6.08	58.86***	46.05*	35.35*	17.77*	−26.49	2.79	66.68***	34.62	63.91*	33.45	30.40	40.81***	29.87*	33.40**
Combination forecast without DFL liquidity index																
Mean	M	2.54***	3.32***	3.04***	2.80***	2.99***	5.59***	1.63**	4.71***	2.43***	7.44***	2.41***	6.12***	2.12***	1.65**	2.85***
	Q	5.35***	6.50***	5.51***	6.41***	5.86***	9.95***	4.27**	7.84***	4.97***	11.78***	4.80***	10.81**	7.74***	6.60***	5.75***
	1	11.32*	13.19**	16.62***	18.92***	16.01***	13.99*	13.27	9.03*	14.46**	20.30**	15.44***	21.05**	12.62**	13.00**	16.07***
Median	M	1.46***	1.86***	2.59***	2.37***	2.45***	3.53***	1.04**	3.10***	1.43***	5.46***	1.75***	4.80***	1.33**	1.19**	1.91***
	Q	2.70**	3.69***	4.42***	4.60***	4.11***	7.09***	2.87**	5.05***	2.71**	7.78***	3.65***	5.93**	5.97***	3.52**	4.61***
	1	5.28*	7.23**	8.03*	9.43**	7.21**	5.48*	9.57*	4.43	9.97**	10.81*	9.70**	8.82	9.00**	5.60	11.20***
Combination forecast with the DFL liquidity index																
Mean	M	2.51***	3.40***	3.09***	2.82***	3.11***	5.62***	1.59**	4.91***	2.42***	8.03***	2.35***	6.41***	2.15***	1.73**	3.00***
	Q	5.29**	6.70***	5.60***	6.63***	6.05***	9.94***	4.22**	8.25***	4.98***	12.46**	4.78***	11.32**	7.88**	7.14***	5.98***
	1	11.30*	14.42**	17.53***	19.52***	16.03***	13.95*	13.33	10.31*	15.19**	21.72**	16.21***	21.53*	13.59***	13.81**	16.81***
Median	M	1.49***	1.96***	2.72***	2.51***	2.51***	3.57***	1.04**	3.19***	1.48***	6.08***	1.77***	5.35***	1.43***	1.31**	2.12***
	Q	2.77*	3.95**	4.65***	5.09***	4.37***	7.10***	2.87**	5.38***	2.78**	9.30**	3.67***	7.41**	6.47***	4.17**	5.11***
	1	5.37*	7.46**	8.65*	10.60**	7.46**	5.44*	9.78*	4.71	10.20**	12.28*	10.06***	10.97	9.60**	5.89	14.76***

the forecasts based on the historical average. In this section, we examine the out-of-sample performance of the predictive model for corporate bonds. We begin with out-of-sample forecasts using single forecasting variables. We set the year 1983 as the beginning of the out-of-sample forecast period.

Table 4 reports the results of out-of-sample forecasts over different horizons. A positive R^2_{OS} value points to an improvement in the out-of-sample forecast by the predictive model, relative to the historical average. When using the CP factors to forecast returns, we re-estimate (11) and (13) for these factors each month using all available data and update them up to that month. The out-of-sample forecast accounts for the small sample bias using the method suggested by Kandel and Stambaugh (1996) and Connor (1997). The statistical significance of R^2_{OS} is evaluated by the p-value of the out-of-sample MSPE-adjusted statistic of Clark and West (2007); standard errors are adjusted by the Hodrick (1992) method.

The left panel of Table 4 reports the results for rating portfolios. The results show that the CP factors and the term spread (*TMS*) have higher out-of-sample forecasting power. Most of the R^2_{OS} values associated with these variables are significantly positive. The CP ten-year factor has larger and more significant R^2_{OS} than the CP five-year factor. The CP factors have higher predictive power for higher-grade bonds. By contrast, the term spread has higher predictive power than the CP factors for lower-grade bonds. Default spreads (*DFS*) have higher predictive power at the one-year horizon.

Liquidity variables also have out-of-sample predictive power. The on-/off-the-run spread has higher predictive power at monthly horizons, whereas changes in money market fund flows ($\Delta MMMF$) have higher predictive power at quarterly horizons than the on-/off-the-run spread. The portfolio's credit spread has predictive power, which is higher for lower-grade bonds at quarterly and yearly horizons. Equity variables have more predictive power for lower-grade bonds but predictive power is unstable with a number of negative out-of-sample R^2s. D/P has higher predictive power at the monthly horizon, whereas stock market return volatility (*Var*) has higher power at quarterly and annual horizons. The growth variable has higher predictive power for BBB and junk bonds.

The right panel of Table 4 reports the results for short- and long-duration portfolios in each rating category. Again, the CP factors and the term spread show higher predictive power and the CP ten-year factor outperforms the CP five-year factor. The CP factor tends to have higher predictive power for short-maturity high-grade bonds, whereas the term spread has higher predictive power for long-maturity low-grade bonds. The on-/off-the-run spread and $\Delta MMMF$ have forecasting power mostly at short-term return horizons. For high-grade bonds (A to AAA), the predictive power of on-/off-the-run spreads is higher for short-maturity bonds, whereas for low-grade bonds, the predictive power is higher for long-maturity bonds. Finally, the portfolio's credit spread has higher predictive power for short-maturity bonds across all ratings.

The results of out-of-sample forecasts for the DFL liquidity index are reported at the bottom of the first panel in Table 4. Results show that it has predictive power at the annual horizon for all bonds except AAA. Thus, the DFL liquidity index appears to have predictive power individually.

In summary, term spreads, CP factors, liquidity factors, and the portfolio's credit spread have higher out-of-sample forecast power than other predictors. D/P has higher predictive power at the monthly horizon and default spreads (*DFS*) have higher power at the annual horizon. Moreover, the predictors have different predictive power for short- and long-maturity bonds. Thus, different predictors appear to track different components of expected returns. This finding suggests that there is room to improve out-of-sample forecast performance by combining individual forecasts. We next explore this possibility.

5.2. Out-of-sample combination forecasts

Table 4 reports the mean and median of independent forecasts by individual predictors when combining forecasts. The results of out-of-sample combination forecasts for rating portfolios are reported in the lower left panel. As shown, combining individual predictors improves the significance of out-of-sample forecasts and increases forecasting stability considerably. R^2_{OS} values of combination forecasts are significant across all ratings and return horizons. The forecast combination produces more stable out-of-sample forecasts across ratings. The out-of-sample predictability tends to be

Table 5
Contributions of the CP factor, liquidity factors, the bond portfolio's credit spread, and DFL in out-of-sample combination forecasts.

This table reports the MHLN statistics of Harvey, Leybourne, and Newbold (1998) for mean and median combination forecasts at monthly (M), quarterly (Q), and annual (1) horizons. We test whether adding the CP 10-year factor, conventional liquidity factors, bond portfolio's credit spread or the Dick-Nielsen, Feldhutter, and Lando (2012) liquidity measure (DFL) into the traditional predictive regression model significantly improves the out-of-sample forecast using the rest of the variables. We adjust the standard errors by the Hodrick (1992) method to account for the impact of overlapping residuals when the return forecast horizon is quarterly and annual. The MHLN test statistics follow the t_{T-k-1} distribution where T is the sample size and k indicates the number of periods ahead for the forecast. Panel A reports results of rating portfolios and Panel B reports results of short- (1) and long-duration (5) portfolios by rating.

Panel A. Rating portfolios

		AAA	AA	A	BBB	Junk	AAA	AA	A	BBB	Junk	AAA	AA	A	BBB	Junk	AAA	AA	A	BBB	Junk
		CP factor					Conventional liquidity factors					Credit spreads (*CSP*)					DFL				
Mean forecast	M	2.64	2.06	1.97	1.36	0.42	2.53	2.36	1.81	1.64	2.31	−0.42	−1.05	0.43	2.84	3.18	−1.88	0.95	0.36	0.25	1.40
	Q	4.80	3.03	2.97	1.32	0.27	−0.37	−0.52	−0.54	−0.65	−0.29	−1.20	−0.34	2.08	3.51	3.77	−1.54	1.05	0.31	0.86	1.05
	1	4.26	3.65	2.44	0.88	0.43	−0.29	−0.47	−0.94	−1.11	−1.21	−1.10	1.11	5.34	4.73	5.68	−0.24	2.02	0.87	0.82	0.06
Median forecast	M	3.32	3.62	2.51	1.76	0.61	3.26	3.08	2.49	2.32	2.72	−0.67	−0.16	0.27	2.93	3.37	−0.56	1.18	0.40	0.23	1.19
	Q	5.40	4.82	3.77	1.82	0.52	0.22	0.24	−0.06	−0.05	0.07	−1.69	1.44	2.48	3.79	3.98	−0.41	1.22	0.41	1.13	0.86
	1	4.28	5.13	3.94	1.88	1.24	0.19	0.04	−0.24	−0.39	−0.39	−0.30	2.88	6.42	5.08	5.60	0.02	1.93	1.11	1.41	1.05

Panel B. Duration portfolios by rating

		Mean forecast										Median forecast									
		AAA		AA		A		BBB		Junk		AAA		AA		A		BBB		Junk	
Predictor		1	5	1	5	1	5	1	5	1	5	1	5	1	5	1	5	1	5	1	5
The CP factor	M	2.16	0.40	2.07	2.23	1.16	1.56	0.47	0.67	0.24	1.14	3.11	2.42	3.25	3.45	1.72	2.43	0.56	1.89	−0.04	1.62
	Q	4.80	1.64	3.52	2.60	1.56	3.15	0.02	1.21	−1.12	1.70	6.09	5.35	4.38	4.39	2.07	4.57	0.39	2.62	−1.54	1.75
	1	5.37	2.18	5.06	3.55	1.72	3.92	−0.36	2.23	−0.99	2.07	5.78	5.82	4.97	4.82	2.42	5.80	0.17	3.51	−0.74	2.14
Conventional liquidity factors	M	3.44	1.31	3.31	1.43	0.87	1.73	−0.35	2.25	0.56	0.35	4.20	1.92	4.11	2.13	1.94	2.49	0.26	2.86	0.87	0.98
	Q	0.03	−0.36	0.28	−0.59	−0.78	−0.55	−0.95	−0.18	−0.69	−0.87	0.39	0.14	0.92	0.11	−0.20	0.03	−0.58	0.32	−0.32	−0.69
	1	−0.24	−0.30	−0.12	−0.51	−0.79	−0.71	−1.03	−0.20	−0.90	−0.85	0.22	0.06	0.27	−0.10	−0.31	−0.12	−0.58	−0.14	−0.34	−1.54
Credit spreads (*CSP*)	M	−0.43	0.28	0.20	−0.05	2.82	−0.33	3.17	0.52	3.51	3.59	−0.71	0.51	0.27	1.20	2.76	0.96	3.08	2.20	3.61	3.88
	Q	1.57	−0.46	1.76	−0.90	2.38	−0.24	2.41	2.84	3.42	2.12	5.54	0.52	2.77	0.37	2.40	1.01	2.45	5.41	3.59	2.18
	1	3.34	−0.29	1.44	0.12	1.88	−0.48	2.25	3.40	3.35	2.00	7.89	1.35	2.27	1.34	1.89	0.91	2.21	4.99	3.29	1.57
DFL	M	0.77	−1.88	1.98	−0.08	1.86	−0.85	0.88	0.55	0.64	2.28	0.99	−1.08	1.89	0.22	2.05	−0.66	1.12	0.37	0.66	2.24
	Q	−0.06	−0.89	2.13	0.05	0.99	−0.07	0.66	1.19	1.49	1.68	0.31	−0.43	2.42	0.29	1.22	0.10	0.94	1.75	1.72	1.60
	1	−0.09	0.29	2.53	0.87	0.79	1.42	0.26	2.43	0.88	1.91	−0.04	0.40	2.77	0.79	0.96	1.32	0.58	2.52	1.27	2.28

higher for lower-grade bonds. Overall, the results show that forecast combination improves the forecasting performance of the model. The out-of-sample forecast R^2_{OS} values are much larger than those reported by Rapach, Strauss, and Zhou (2010) for stock returns at annual forecasting horizons, indicating that corporate bond returns are more predictable than stock returns.

The results of duration portfolios by rating reported in the right panel of Table 4 show a similar improvement by combination forecasts. R^2_{OS} values are significant across all maturities and ratings. A clear advantage of using forecast combination is that it improves the reliability of out-of-sample forecasting. Mean combination forecasts show that short-maturity bond returns are generally more predictable than long-maturity bond returns, particularly for investment-grade bonds.

We next calculate the MHLN statistics of Harvey, Leybourne, and Newbold (1998) to test whether the combination forecast by certain variables encompasses that by adding other variables. These tests assess whether the marginal contribution of the CP factor, liquidity factors, and the bond portfolio's credit spread to the out-of-sample forecast power of the model is significant or not by controlling the effects of other predictors.

Table 5 reports the MHLN statistics for combination forecasts. Panel A shows that the CP factor contributes significantly to the out-of-sample forecasting power for investment-grade bond returns across all horizons beyond other predictors. Conventional liquidity factors significantly contribute to the out-of-sample forecasting power of the model at the one-month horizon. The portfolio's credit spread makes a significant contribution to the forecasting power for lower-grade bonds beyond all other predictors. On the other hand, we found that equity variables do not add a significant contribution to the forecasting power (omitted for brevity).[23] We also considered other predictors such as inflation and the book-to-market ratio as additional predictors. These variables have been shown to have predictive power for stock returns by Fama and Schwert (1977) and Ferreira and Santa-Clara (2011). However, we found that adding these predictors did not improve the predictive power of the model either. Overall, the results show that the CP factor, liquidity factors, and the bond portfolio's credit spread contain important information for variations in the expected returns of corporate bonds over and beyond that contained in the traditional predictors.

Panel B of Table 5 reports results for bond portfolios with different durations in each rating category. The results again show that the CP factor contributes significantly to out-of-sample forecasts for returns of investment-grade bonds across durations. Liquidity factors forecast corporate bond returns at short horizons (monthly) across durations. The bond portfolio's credit spread significantly contributes to the predictive power of the model for short-maturity bonds across all ratings at quarterly and yearly horizons, and for long-maturity BBB and junk bonds at most return horizons.

The earlier results show that the DFL liquidity index has predictive power individually. However, it is unclear whether combining it with other predictors will significantly contribute to the total out-of-sample predictive power of the model. To examine this issue, we perform a combination forecast by including the DFL liquidity index and test whether adding the DFL liquidity index can significantly improve the predictive power of the model.

To see if adding the DFL liquidity index significantly improves the predictive power of the model, we report the results of MHLN tests for rating and duration portfolios in Panels A and B of Table 5. Results show that MHLN statistics for the DFL index are positive in most cases. However, for the rating portfolios in Panel A, the increase in the predictive power of the model is not significant except in one case (AA bonds at one-year horizon). For the duration portfolios in Panel B, the significance of incremental predictive power concentrates on only short-duration AA bonds and long-duration junk bonds. The message from this encompassing test is that while the DFL has predictive power individually, its contribution to the total predictive power of the model is not strong when it is combined with other predictors. One possible reason for this result is that the time span of the DFL liquidity series is relatively short due to the requirement of transaction data, which weakens the statistical power.

Dick-Nielsen, Feldhutter, and Lando (2012) find that credit spreads contain a significant liquidity component. To see whether the liquidity effect may drive the predictive power of the bond's credit

[23] These variables include equity return predictors in Table 2.

spread, we calculate the liquidity-adjusted spread by running the regression of credit spreads against the DFL liquidity for each rating/duration portfolio and using the credit spreads adjusted for the liquidity effect in the in- and out-of-sample forecasts. The results (omitted for brevity) show that the liquidity-adjusted credit spreads continue to have predictive power for corporate bond returns up to the one-year horizon and the predictive power is higher for lower-grade bonds, consistent with the findings for the unadjusted portfolio credit spread. Thus, the predictive power of the bond's credit spread does not appear to be driven by the liquidity effect.[24]

In summary, both in- and out-of-sample results show evidence of corporate return predictability. Variables that are related to term structure and business and credit market conditions are shown to have predictive power. In addition, the results show a time-varying liquidity component in expected corporate bond returns that is predictable. The liquidity factors track variations in the liquidity component of expected bond returns at short horizons. The results show that variations in expected corporate bond returns have a rich mix of default, interest rate, and liquidity risk components, and combination of individual forecasts improves the performance of the predictive model.

5.3. Economic significance

To assess the economic significance of return predictability, we calculate the utility gains accrued to investors who use the predictive model to forecast returns. Table 6 reports changes in average utility from the forecasts of predictive regressions over the forecasts using the historical mean up to the one-year horizon. All numbers are annualized. In the individual forecast, for the conventional liquidity variables, we focus on the on-/off-the-run spread as it dominates $\Delta MMMF$ and other liquidity variables. We report the results of individual forecasts, as well as the combination of individual forecasts. The left panel reports results for rating portfolios and the right panel reports results for duration portfolios in each rating category.

The left panel of Table 6 shows that utility gains are overwhelmingly positive across ratings for the CP factor, on-/off-the-run spreads, term spreads (*TMS*), and growth. Utility gains are positive for the portfolio's credit spread (*CSP*) for all bonds except AAA. *D*/*P*, *E*/*P*, and stock return volatility (*Var*) generally have positive utility gains for high-grade bonds. Using combination forecast produces much more stable results (Panel B). Utility gains of combination forecasts are overwhelmingly positive across all ratings and return horizons, indicating clearly that return predictability is economically significant. The utility gains are greater than those reported for stock return forecasts (Rapach, Strauss, and Zhou, 2010), indicating that corporate bond return predictability is more significant economically. The results strongly suggest that mean-variance bond investors have higher utility gains by using the information in the predictive model. The number can also be interpreted as the portfolio management fee (in annualized percentage returns) that an investor is willing to pay to have access to the information available in a return forecast model. As an example, when the return horizon is monthly and mean combination forecasting is used, the mean-variance investor will be willing to pay up to about 3% annualized fee when investing in BBB bonds using the combination forecast.

The right panel of Table 6 shows that utility changes for investors of bonds with short- and long-durations. Again, the forecast combination produces more stable forecasts and the utility gains are overwhelmingly positive across maturities. Economic gains tend to be more significant for the forecast of long-duration bonds. Here we see more clearly that a distinct advantage of the combination method is its ability to produce more reliable and consistent forecasts, compared with the results of individual forecasts for duration portfolios in Panel A. Overall, the results show that the magnitude of the gains from the predictive model is economically meaningful for bond investors.

Table 6 also shows the results of economic significance associated with the forecasts using the DFL liquidity index. Panel A shows the results based on the individual forecast. The results show that the predictive power of the DFL liquidity index is economically significant for all rating portfolios.

[24] For example, at the annual horizon, the in-sample regression coefficients (*t*-values) of the adjusted credit spread are -0.09 (-0.44), 0.26 (3.62), 0.33 (3.16), 0.35 (3.49), and 0.24 (3.16) for AAA, AA, A, BBB, and junk bonds, respectively and the adjusted R^2 values are comparable to those for the unadjusted credit spread reported in Table 2. Also, for the out-of-sample individual forecast using the adjusted spread as the predictor, the R^2_{OS} values are all significant at the 1% level for all bonds except AAA, similar to those reported in Table 4.

Table 6
Economic significance.

This table reports annualized utility gain (in percentage) from a forecast of the predictive regressions over that using the historical mean. We only report the results of the regression associated with the predictors that have higher predictive power and combination forecasts. The predictors include the dividend yield (*D/P*), earnings–price ratio (*E/P*), stock return variance (*Var*), growth ratio (*Growth*), term spread (*TMS*), default spread (*DFS*), CP ten-year factor (*CP10*), on-/off-the-run spread (*Onoff*), the rating and duration portfolio's credit spread (*CSP*), and the Dick-Nielsen, Feldhutter, and Lando (2012) liquidity measure (DFL). The portfolios are rebalanced each month. In each month, we sort all bonds independently into five rating portfolios and five duration portfolios (1 is short- and 5 is long-duration). A total of 25 duration portfolios are constructed at the intersection of rating and duration sorts. We use the data in the past ten years (rolling) to estimate portfolio variance. Panel A reports results of individual forecasts, and Panels B and C report results of combination forecasts without and with the DFL liquidity measure.

Panel A. Individual forecasts

		Rating portfolios					Duration portfolios									
		AAA	AA	A	BBB	Junk	AAA		AA		A		BBB		Junk	
							1	5	1	5	1	5	1	5	1	5
D/P	M	0.39	0.55	0.49	0.12	−1.19	−0.67	−0.11	−0.89	0.33	−1.13	0.01	−0.91	0.30	−0.26	−1.77
	Q	1.15	0.52	0.52	−0.10	−1.05	−0.77	−0.37	−1.09	0.90	−1.43	0.20	−0.69	0.58	0.44	−3.29
	1	0.77	0.22	0.31	−0.14	−1.07	−0.52	−0.59	−0.64	0.52	−0.98	0.53	−0.59	−0.32	0.06	−2.52
E/P	M	1.01	1.34	1.26	−0.34	−1.07	0.62	−0.46	−1.14	1.12	−1.05	1.43	−0.96	0.72	1.32	−4.15
	Q	1.58	1.52	1.01	0.71	0.86	−0.21	−0.83	−1.31	1.51	−0.79	1.63	0.39	1.42	1.32	−2.04
	1	−0.02	0.43	0.64	1.08	1.15	−1.28	0.61	−0.41	1.24	0.08	0.80	0.49	0.53	1.50	0.26
Var	M	1.28	1.85	0.71	−0.55	−1.29	−0.66	0.82	−0.74	1.84	−1.00	0.77	−1.10	0.36	−0.77	−1.73
	Q	2.30	2.12	1.12	0.13	−1.13	−1.32	1.20	−1.73	2.50	−1.35	1.30	−0.49	1.20	0.02	−1.97
	1	0.32	0.56	0.41	−0.19	−0.73	−0.23	0.04	−0.35	0.78	−0.45	−0.20	−0.24	−0.13	−0.24	−0.28
Growth	M	1.40	1.28	1.59	1.26	0.51	0.94	−1.51	0.60	0.44	0.10	2.12	−0.08	1.30	−0.02	1.11
	Q	0.52	1.35	0.92	1.46	2.22	0.10	−1.52	−0.42	0.54	−0.76	2.38	0.60	1.78	1.81	−1.22
	1	0.97	1.00	0.96	1.84	1.73	−0.51	−1.17	−0.49	−0.11	−0.60	1.42	0.39	1.53	1.16	−0.83
TMS	M	1.65	1.35	1.72	0.66	0.60	0.18	0.85	−0.07	2.57	0.20	2.29	0.43	2.64	0.89	0.98
	Q	1.30	1.37	2.24	2.48	0.59	−0.37	0.78	−0.15	2.36	−0.15	2.15	1.07	3.18	1.20	0.45
	1	1.00	1.58	2.43	2.56	0.19	0.02	−0.13	−0.34	2.10	−0.17	2.20	0.92	2.06	1.06	0.11
DFS	M	−0.08	0.69	0.01	−0.85	−4.28	−1.34	−0.12	−1.76	−0.25	−1.93	−0.23	−2.05	−0.53	−2.41	−5.19
	Q	0.18	0.54	0.18	−0.45	−2.20	−1.97	0.10	−2.01	−0.17	−2.01	−0.26	−1.28	−0.13	−0.32	−5.32
	1	0.93	0.38	0.10	−0.44	−1.99	−1.53	0.03	−1.89	0.66	−1.87	0.41	−1.26	0.46	−0.38	−5.25
CP10	M	3.25	2.48	2.82	1.91	−0.59	1.10	0.95	−0.25	2.27	−0.70	2.49	−1.10	1.13	−1.85	−0.30
	Q	3.66	3.22	3.29	2.31	0.18	0.73	2.58	−0.34	3.56	−1.10	4.17	−0.81	2.67	−1.06	−1.21
	1	3.84	2.80	2.94	2.41	0.53	0.57	3.67	−0.46	4.14	−1.14	4.87	−1.00	2.66	−0.81	−1.98
Onoff	M	3.75	3.57	3.59	3.56	4.28	1.86	2.60	1.22	3.62	0.60	4.22	0.43	4.24	2.03	2.67
	Q	3.37	2.95	3.83	3.64	3.89	1.16	1.12	0.64	1.53	0.35	2.60	1.13	2.93	1.48	1.80
	1	3.35	2.74	3.13	2.85	2.85	0.38	0.94	0.16	1.24	0.07	2.11	0.95	2.21	1.04	0.61
CSP	M	0.35	1.20	0.30	1.30	1.10	0.20	0.05	−0.77	0.92	−0.12	1.47	−0.45	−0.14	0.84	1.88
	Q	−0.34	0.14	1.78	1.69	3.54	0.03	0.00	−0.77	0.01	−0.41	1.77	0.41	1.93	2.73	−0.15

Table 6 (*continued*)

Panel A. Individual forecasts

		Rating portfolios					Duration portfolios									
		AAA	AA	A	BBB	Junk	AAA		AA		A		BBB		Junk	
							1	5	1	5	1	5	1	5	1	5
	1	−0.17	0.17	1.82	1.64	3.64	0.28	0.19	−0.89	0.29	−0.50	1.36	0.19	1.03	2.77	−1.98
DFL	M	0.26	1.48	2.48	0.79	1.98	0.68	−1.41	0.39	0.26	0.53	−0.69	0.00	−2.16	−0.81	−0.17
	Q	0.30	0.85	1.31	1.09	4.00	0.59	−1.32	0.55	0.09	0.47	−1.03	1.97	1.25	5.14	2.08
	1	0.49	1.36	1.61	1.72	2.03	0.29	0.53	0.55	0.66	0.57	1.80	2.55	−0.03	3.38	0.22

Panel B. Combination forecasts without the DFL liquidity index

		Rating portfolios					Duration portfolios									
		AAA	AA	A	BBB	Junk	AAA		AA		A		BBB		Junk	
							1	5	1	5	1	5	1	5	1	5
Mean	M	2.63	3.14	3.16	2.99	2.19	1.00	1.12	0.87	2.25	0.59	2.49	0.43	2.14	−0.13	1.85
	Q	3.00	3.40	3.38	2.59	2.17	0.63	1.31	0.29	2.39	0.08	2.71	1.53	2.85	1.52	1.15
	1	2.46	2.61	2.98	2.57	1.79	0.61	1.15	0.14	2.02	0.09	2.62	1.15	1.93	0.86	0.03
Median	M	1.01	1.16	2.24	2.02	2.19	0.85	0.08	0.72	0.61	0.66	1.43	0.73	0.78	0.32	0.88
	Q	1.87	1.20	3.05	1.67	1.30	0.62	0.02	−0.06	0.40	−0.34	1.76	1.14	2.00	0.70	0.18
	1	1.17	0.93	1.90	1.18	1.07	0.30	0.12	0.13	0.54	0.01	0.99	0.88	1.98	0.36	0.14

Panel C. Combination forecasts with the DFL liquidity index

		Rating portfolios					Duration portfolios									
		AAA	AA	A	BBB	Junk	AAA		AA		A		BBB		Junk	
							1	5	1	5	1	5	1	5	1	5
Mean	M	2.62	3.05	3.12	2.94	2.18	1.00	1.03	0.87	2.25	0.59	2.39	0.43	2.08	−0.09	1.85
	Q	2.98	3.33	3.39	2.60	2.21	0.63	1.28	0.29	2.32	0.08	2.61	1.52	2.90	1.73	1.15
	1	2.42	2.54	2.99	2.58	1.86	0.61	1.17	0.14	2.13	0.09	2.67	1.15	1.97	0.88	0.03
Median	M	1.12	1.25	2.26	2.01	2.11	0.85	0.08	0.73	0.66	0.64	1.40	0.72	0.79	0.30	0.88
	Q	1.98	1.17	3.10	1.79	1.56	0.58	0.00	−0.05	0.43	−0.33	1.74	1.11	2.43	0.94	0.28
	1	1.26	0.93	1.97	1.37	1.07	0.30	0.18	0.13	0.51	0.01	1.03	0.92	1.94	0.47	0.14

In addition, the forecasts of combining the DFL liquidity index are of economic significance (Panel C). The results show that including the DFL as a predictor adds economic value to investors.

For robustness, we also calculate changes in the Sharpe ratio (Sangvinatsos and Wachter, 2005) and the risk-adjusted abnormal return measure (Goetzmann et al., 2007) from the forecast of predictive regressions relative to that of a naïve model based on historical mean. The results (omitted for brevity) again show that using the predictive model to forecast returns consistently increases the risk-adjusted return of investors. Thus, our tests of economic significance of corporate bond return predictability are robust to different performance measures.

5.4. Potential survivorship bias

A potential concern is that our results may be subject to survivorship bias. In the database, bonds can be delisted because of defaults or other reasons. We assume that the return or price for a bond on the last date listed in the dataset is the final return or price for that bond (Gebhardt, Hvidkjaer, and Swaminathan, 2005a, 2005b; Jostova et al., 2013). This can introduce a problem into the calculation of returns for delisted bonds as we do not have the record of recovery rates or losses given defaults for individual bonds in the databases. However, the average annual percentage of bonds delisted is less than 1% over the whole sample period. Thus, survivorship is unlikely to drive the predictability results.

To assess the potential survivorship bias, we undertake two measures. First, we conduct the subperiod analysis over the periods with different delisting rates to see if the results are sensitive to the survivorship. Second, we adjust returns of defaulted bonds by recovery rates documented in the literature (Altman and Kishore, 1998; Moody's Investors Service, 2011) and use these adjusted returns in our empirical tests. If the survivorship is indeed an important concern, there should be a substantial difference between the results for the unadjusted and adjusted returns.

To conduct the sensitivity analysis, we first divide the whole sample period into two subperiods. Over our sample period, the delisting rates are higher after 1990.[25] We use December 1990 as the cut-off to divide the sample period into two subperiods. We introduce a dummy slope variable $DM_t = 1$ after 1990 and 0 otherwise, and run the following in-sample regression at the annual horizon:

$$\begin{aligned} r_{t+1} = {} & \alpha + (\beta_1 + D_1 DM_t) CP10_t + (\beta_2 + D_2 DM_t) TMS_t \\ & + (\beta_3 + D_3 DM_t) DFS_t + (\beta_4 + D_4 DM_t) Onoff_t + (\beta_5 + D_5 DM_t) Var_t \\ & + (\beta_6 + D_6 DM_t) Growth_t + (\beta_7 + D_7 DM_t) CSP_t + \varepsilon_{t+1}. \end{aligned} \tag{13}$$

This regression model is an extension of Model 4 in Table 3 (see the bottom panel) and includes the subperiod dummy variables. If survivorship bias is a serious concern, we should see that the coefficients of the dummy variables are significant to reflect the difference in the delisting rates between the subperiods.

The results (omitted for brevity) show that none of the dummy variables are significant. This finding shows that in-sample return predictability is not sensitive to delisting bias. The impact of survivorship is expected to be more serious for low-grade bonds. However, the results show that the dummy variables are not significant for low-grade bonds and the adjusted R^2 values are very close to those reported in the last panel of Table 3.[26] We also add a similar dummy slope variable (equal to 1 after 1990) in the out-of-sample forecasts for each individual predictor and then obtain the mean and median combination of individual forecasts. The results continue to show no material differences in the out-of-sample performance for all rated bonds even after allowing for the slope coefficient of the out-of-sample regression to be different after 1990. These findings indicate that the effect of delisting bias is minor.

Moreover, we adjust the return by the default rate π_t and the loss rate given default L and use the adjusted return to perform in- and out-of-sample forecasts. The default-adjusted return can be expressed as $r_t^{adj} = r_t - \pi_t L$ where it accounts for the loss rate upon default. Again, the results (omitted for brevity) show no material changes in the in- and out-of-sample performance for bonds in all rating

[25] Average delisting rates are 0.36% from 1973 to 1990 and 1.09% from 1991 to 2010.

[26] Junk bonds accounts for about 38% of the delisted bonds.

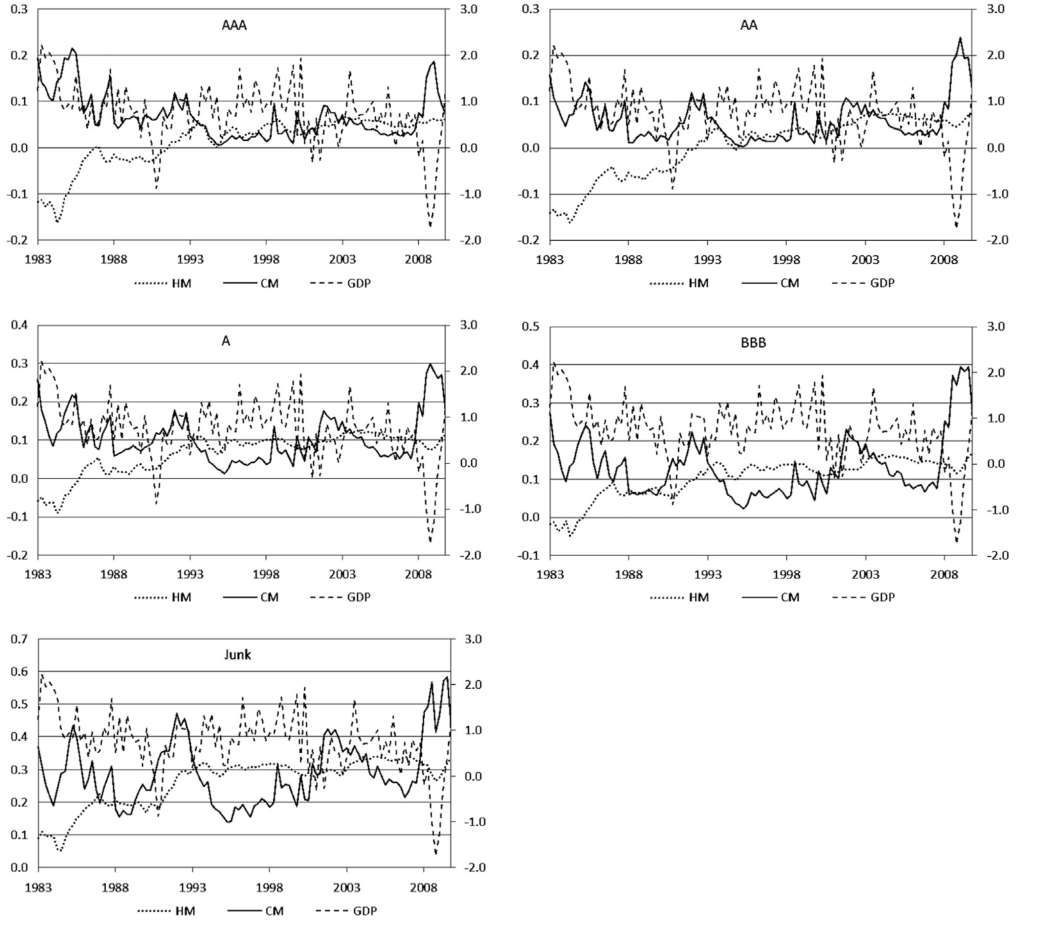

Fig. 1. Bond premium forecasts and GDP growth.
This graph plots the out-of-sample forecasts of quarterly premiums by historical average (HM), the mean combination forecast method (CM), and the GDP growth between 1983 and 2009.

categories after accounting for the loss given default in portfolio returns. Overall, the results indicate that the effect of delisting bias is unlikely to drive the predictability of corporate bond returns.[27]

5.5. Business cycles and out-of-sample forecasts

An important question is what drives the predictability of asset returns. Fama and French (1989) and Cochrane (2007) suggest that heightened risk aversion during economic downturns requires a higher risk premium, thereby generating equity premium predictability. Gilchrist and Zakrajsek (2012) find that credit spreads (excess bond premium) has strong predictive power for business cycles. Næs, Skjeltorp, and Odegaard (2011) find that stock market liquidity contains useful

[27] We use annual default rates published by rating agency. As Standard and Poor's only provides the annual default rate since 1980, we use the annual default rate before 1980 from Moody's. Moody reports that over the period of 1982–2010, the average recovery rate is 43% for investment-grade bonds and 38% for junk bonds. We therefore use loss rates of 57% for investment-grade bonds and 62% junk bonds. We also tried the recovery rates reported by Altman and Kishore (1998) and found that the results are quite similar.

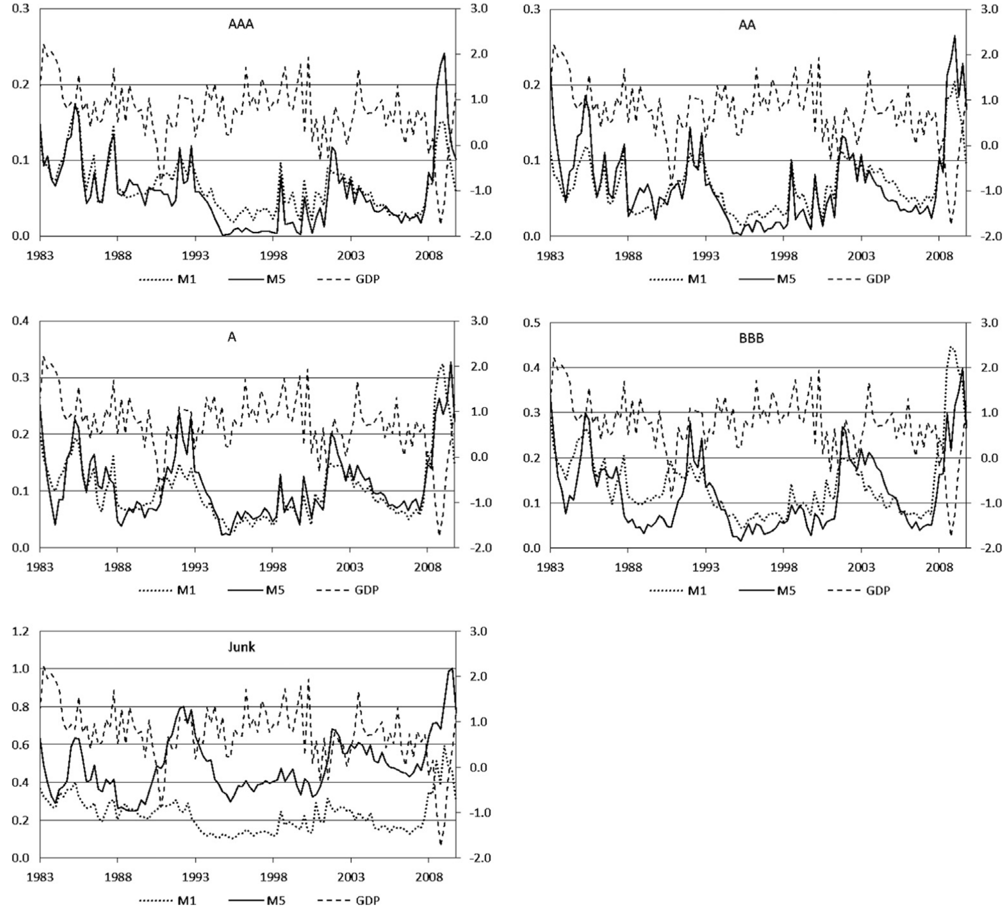

Fig. 2. Premium forecasts of maturity portfolios by rating and GDP growth.
In this figure, we plot the out-of-sample forecast of quarterly premiums of portfolios with the shortest duration (M1) and the longest duration (M5) in each rating category by the mean combination forecast method, and the GDP growth between 1983 and 2009.

information for the current and future state of the economy. These findings suggest that an important reason that the predictors used in this study have predictive power is because they contain credible signals for the evolution of the real economy and risks in economic outlook. In this section, we investigate whether forecasts of the bond premium are linked to the economy. The large data sample permits us to examine this issue for bonds with different maturities in each rating category. We use GDP growth as the measure of business conditions. Since this data item is only available quarterly, we perform quarterly forecasting to match the time interval.

In Fig. 1, we plot out-of-sample risk premium forecasts and GDP growth. We also plot the out-of-sample forecasts of quarterly premiums by both historical mean (HM) and mean combination forecasts (CM), as well as GDP growth from 1983 to 2009. The historical mean is updated each quarter to the time of forecast. The results show a negative correlation between GDP growth and bond risk premium forecasts. There are three significant downward spikes of GDP growth during this period, which occur in 1990, 2001, and 2008. These downward spikes correspond to three business cycles reported by the NBER, which are from July 1990 (peak) to March 1991 (trough), from March 2001 (peak) to November 2001 (trough), and from December 2007 (peak) to June 2009 (trough). Fig. 1 shows that the risk premium of corporate bonds generated from the combination forecast is related to the economy. The risk premium increases during the economic downturn. The results support the hypothesis that when economic growth is low, investors become more risk averse and so require a higher risk premium. Variations in the risk premium are higher for lower-grade bonds. By contrast, the historical mean approach gives a flat risk premium forecast, which is not sensitive to business conditions.

In Fig. 2, we plot the out-of-sample risk premium forecasts of long- and short-duration bond portfolios and GDP growth. As shown, variations in the risk premium are higher for long-duration bonds (M5) than for short-duration bonds (M1). Overall, the results show that risk premiums estimated from the predictive model are higher for both low-grade bonds and long-maturity bonds. Moreover, variations in corporate bond risk premiums of the combination forecasts are linked to the real economy. The results show that the selected variables collectively are valuable for corporate bond risk premium forecasts. Combining these predictors generates forecasts more plausibly related to macroeconomic risk than those based on the historical average. Our findings are consistent with the contention that the predictability of corporate bond returns is generated by time-varying risk premiums due to changing business conditions.

6. Conclusions

The predictability of asset returns has been a subject of extensive research over the past several decades. A large body of empirical research has documented important findings that have dramatically contributed to our understanding of asset pricing and risk premium determination. The predictable components in asset returns uncovered in empirical work have led to the development of theoretical equilibrium models to accommodate the stylized fact of return predictability and its effect on dynamic asset allocation. However, much of the focus in the literature is on the predictability of equity returns and variations in the equity risk premium. The issue on the predictability of corporate bond returns is underexplored. In this paper, we examine this issue using a comprehensive data sample of corporate bonds and document a number of unique findings that contribute to the literature.

We find that the Cochrane-Piazzesi (2005) forward rate factor, liquidity factors, and the bond's credit spread have predictive power for corporate bond returns. Corporate bond returns are more predictable than stock returns. The predictability of bond returns varies by rating and duration of corporate bonds. Return predictability is higher for low-grade bonds. Controlling for the effect of ratings, returns are generally more predictable for short-term bonds. Including the forward rate and liquidity factors and the bond portfolio's credit spread along with traditional forecasters significantly improves the predictive power of the model. The results show that variations of expected corporate bond returns have a rich mix of components that are related to term structure and the business and liquidity conditions.

The predictability of corporate bond returns is statistically significant and economically meaningful. The predictive model outperforms the historical average forecast out-of-sample. The predictive model generates significant utility gains and the combination method provides more reliable forecasts. The finding for the economic significance of return predictability is robust to different measures of performance.

The forecast of the corporate bond risk premium is linked to macroeconomic fundamentals. We find that forecasts of corporate bond risk premiums are related to business cycles. The risk premium of long-maturity bonds is more sensitive to changes in the economic condition than that of short-maturity bonds. Out-of-sample forecasts by the predictive model produce measures of corporate bond risk premiums that are more plausibly related to macroeconomic risk than historical average forecasts. The results indicate that time variations in risk premiums associated with changing business conditions are the driving force behind the predictability of corporate bond returns.

Our findings have implications for theoretical modeling and asset pricing research. In particular, we show that the pricing model of defaultable bonds should account for the phenomenon of return predictability in order to explain the dynamics of yield spreads more satisfactorily. The predictability of corporate bond returns uncovered in this study is also relevant to theoretical and empirical asset allocation research. Understanding how return predictability affects dynamic asset allocation between bonds and stocks is an important extension for a future study.

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