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Credit Spreads, Business Conditions, and Expected Corporate Bond Returns

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Abstract: Using an aggregate credit spread index, we find that it has substantial predictive power for corporate bond returns over short and long horizons. The return predictability is economically and statistically significant and robust to various controls. The credit spread index and its components have more predictive power for bond returns than conventional default and term spreads. When decomposing the credit spread index into investment- and speculative-grade components, the latter has more predictive power for future bond returns. The source of the index's predictive power is from its ability to forecast future economic conditions.

Keywords: credit spreads; default risk; corporate bonds; return predictability; economic conditions

1. Introduction

Credit markets have provided some of the most valuable information, which has been shown to be superior to stock market information, for predicting future economic conditions (see Fama and French 1989, 1993; Gilchrist and Zakrajsek 2012; Guo et al. 2019). Financial intermediaries play an important role in supplying funds to the economic system. Changes in the capital position of financial intermediaries can have significant impacts on the supply of credit and cost of debt financing and consequently, on consumer spending, production, and the performance of real economy. Academicians and practitioners have long relied on credit spreads—differences in the yields between various corporate debt instruments and government debts of equal maturity—to extract expectations of future business conditions. Credit spreads serve as a gauge of the strain in the financial system and lending risk, which have important economic consequences. Through this vital role, changes in credit spreads can provide credible signals for business risk and future economic conditions.

In a seminal paper, (Gilchrist and Zakrajsek 2012) propose a new credit spread index—the so-called "GZ credit spread"—from individual corporate bonds yield spreads, and demonstrate that this index has high predictive power for future economic activity. They find that this index is a more powerful predictor for future economic activity than any other credit spread predictors used in the literature, e.g., BAA-AAA corporate bond spreads, and commercial paper-Treasury spreads, etc. Given the superior performance of the GZ index in predicting future economic conditions, a question that naturally arises is whether this index also has power for forecasting asset returns.

This paper explores the ability of the GZ credit spread index to predict corporate bond returns. Credit risk is the most important determinant of risky bond returns (see Longstaff et al. 2005; Lin et al. 2011; Chung et al. 2019). Modern asset pricing theory suggests that time-varying risk premiums associated with changing business conditions are a driving force for return predictability. If the GZ index is a powerful forecaster for macroeconomic performance, it should have high predictive power for future bond returns. However, return predictability also depends on other variables such as interest rates, term spreads, and firms' expected cash flows (see Rapach et al. 2010). Thus, although GZ has shown that their credit spread index is an effective forecaster for future economic activity, it is not clear whether this predictive ability will translate into a high predictive power for future bond returns over and beyond usual predictors.

The question of whether the GZ spread index has predictive power for returns is of interest in and of itself, but perhaps a more interesting issue is how the GZ index may fare against traditional credit spread variables such as default spreads, commercial paper yield spreads, issuer quality, and bond-level yield spreads in return predictability. Previous studies have found that these variables can also predict future asset returns. The issue at hand is not only whether the GZ credit spread index will perform better than traditional credit spread variables, but also in what capacity it drives future returns. If the GZ credit spread captures information not available in other predictors, it would be beneficial to combine the GZ spread with them to improve the performance of a predictive model.

In this paper, we examine the predictive power of the GZ index and traditional credit market predictors for corporate bond returns. Our focus on corporate bond predictability is motivated by several reasons. First, credit spread measures are constructed from the bond market data. If these measures have any predictive power, it should be more clearly manifested in the bond market. Second, the literature for corporate bond return predictability is small. Although it has been shown that credit spreads can predict stock returns, this issue is considerably underexplored in the corporate bond market. Given that the debt market is much larger than the equity market and is the most important venue for corporate long-term financing, it is essential to understand return predictability in this market.

We evaluate the predictive power of the GZ credit spread index relative to other return predictors, which include traditional default spread and term structure variables (see Fama and French 1993; Greenwood and Hanson 2013). Moreover, we conduct combination forecasts by combining the GZ index with other predictors to see if it can further improve the out-of-sample performance. Previous studies have found that different predictors contain different sources of information for asset returns (see Rapach et al. 2010). As such, combining different predictors has a potential to generate better forecasts.

We uncover the new evidence that the GZ credit spread index and its components have superior predictive power for future returns. Predictability is higher for low-rated and short-maturity bonds. Return predictability is of economic significance and is robust to controlling for asset return correlations and transaction costs. Corporate bond return predictability is closely related to business cycles; return predictability is stronger when economic conditions are poor. The GZ index calculated from high-yield bond data contains more information to predict corporate bond returns than the GZ index based on investment-grade bonds. One possible reason is that speculative-grade bond yield spreads are more sensitive to changes in economic conditions and therefore, provide better signals for future economic performance and returns.

Combining the GZ variables with term structure variables generates better forecasts for corporate bond returns. However, combining the GZ variables with other conventional credit spread variables produces no significant forecast gains. The results suggest that the GZ variables encompass the information in traditional credit spread variables. Finally, including macroeconomic and policy uncertainty variables in the predictive regression further improves the forecast performance. More importantly, we find that the GZ variables contain valuable information for future corporate bond returns over and beyond that embedded in macroeconomic and policy uncertainty variables.

The remainder of this paper is organized as follows. Section 2 provides a literature review. Section 3 discusses our empirical methodology and test procedure. Section 4 describes the data and Section 5 reports empirical results. Finally, Section 6 summarizes our major findings and concludes the paper.

2. Literature Review

A large literature dated back to (Dow 1920), has investigated whether asset returns are predictable. (Welch and Goyal 2008; Rapach et al. 2010) provide a nice summary of prior research. Despite enormous efforts devoted by academic researchers in past several decades, return predictability remains controversial. (Welch and Goyal 2008) examine a long list of predictors from the literature and find that they cannot provide better stock return forecasts than a simple forecast based on the historical mean return. On the other hand, a number of studies have shown that returns are predictable (see, for example, Rapach et al. 2010; Thornton and Valente 2012; Gargano et al. 2019). The vast literature has focused on the predictability of stock and Treasury bond returns. Only a few studies examine the time-series predictability of corporate bond returns (see Keim and Stambaugh 1986; Fama and French 1989; Lin et al. 2014, 2018)).

Among a long list of return predictors, credit spread variables have attracted considerable attention from financial researchers. (Fama and French 1989) are the first to show that default spreads contain important information for expected returns. They find that variations in default spreads are closely related to long-term business conditions that span over several business cycles. They suggest that default spreads capture time-varying risk premiums induced by shocks to economic fundamentals. Since the pioneering work of (Fama and French 1989), voluminous studies have explored the predictive information content of conventional credit spread measures (see, for example, (Friedman and Kuttner 1992; Emery 1996; Gertler and Lown 1999; Welch and Goyal 2008; Gilchrist et al. 2009; Rapach et al. 2010; Greenwood and Hanson 2013; Lin et al. 2014). It has been shown that conventional credit spreads have predictive power for future asset returns.

In a seminal paper, (Gilchrist and Zakrajsek 2012) construct a new credit spread index directly from individual bond spreads and find they have superior predictive power for future economic conditions. Since risk premiums vary with economic conditions, this finding raises an issue of whether their credit spread index can predict asset returns better than conventional credit spread measures. In this paper, we examine this issue using corporate bond return data. To our knowledge, no prior research has investigated the predictive power of the GZ index for asset returns. Our work represents the first study on this issue in the corporate bond market.

3. Empirical Methodology

This section outlines our empirical methodology. We use predictors at time t to forecast future corporate bond returns over different horizons (k) using the following predictive regression:

$$r_{t,k} = \delta_0 + \delta_1 X_t + \epsilon_{t,k}, \quad (1)$$

where $r_{t,k}$ is the return of corporate bonds between time t and $t+k$, X_t is a vector of predictors, and $\epsilon_{t,k}$ is the error term. The dependent variable can be the excess return or the credit spread component of corporate bond returns. The former is the return of a corporate bond in excess of one-month Treasury bill rate whereas the latter is the bond return in excess of the return of a risk-free asset (Treasury) with the same maturity. Using the credit component of returns allows us to separate its predictability from that of the interest rate component in corporate bond returns.

Our baseline analysis includes three sets of predictors. The first set of variables consists of the GZ-family predictors, which are constructed using the method suggested by (Gilchrist and Zakrajsek 2012). These variables include actual GZ spreads (AGZ), predicted GZ spreads without an option adjustment (PGZ1), predicted GZ spreads with an option adjustment (PGZ2), and the excess bond premium (EBP). The second set of variables contains term structure predictors such as the short-term interest rate level (TBL) and the term spread (TMS) or the slope of yield curve. The third set consists of conventional credit spread predictors used in the literature, such as default spreads (DFS), commercial paper spreads (CPS), and bond issuer quality (IQ).[1] We compare the ability of these variables to predict corporate bond returns in and out of sample. In an extended analysis, we further investigate the role of macroeconomic and policy uncertainty variables in bond return predictability.

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1 These predictors are explained in detail in the data section.

(Gilchrist and Zakrajsek 2012) show that their credit spread variables have substantial predictive power for future economic activity. As asset risk premiums are closely linked to economic conditions, high during the economic downturn and low during the economic expansion, any variable that can predict economic conditions stands a good chance to have predictive power for asset returns. We therefore examine whether the GZ variables have higher predictive power than traditional credit spread variables.

The GZ credit spread variables are constructed by yield spreads from a broad base of individual bonds. The construction of these variables involves two steps (see Appendix A for the detailed procedure). The first step is to calculate the credit spread of an individual corporate bond and average them across bonds in the sample each month. This step involves estimating the yield of an equivalent risk-free security with identical cash flow and maturity as the corporate bond, and subtracting it from the promised yield of the corporate bond to generate the credit spread. The second step is to decompose the credit spread into the expected and unexpected components for each individual bond and then aggregate them across bonds. The expected component is obtained by regressing the credit spread of each bond against the distance-to-default of the (Merton 1974) model, bond duration, issuance amount, coupon rate, and bond age. The difference between the credit spread index obtained in step one and the expected spread index in step two is the unexpected component of credit spreads, which is dubbed the excess bond premium (EBP) by (Gilchrist and Zakrajsek 2012).

Many corporate bonds in our sample include a call provision. To control for the effect of bond call option, we include the call provision (indicator), interest rate volatility, and term structure variables in the regression to capture these effects on the predicted component of credit spreads. Then, following the same procedure above, we obtain the expected and unexpected components of aggregate credit spreads. We denote the predicted GZ spread without the option adjustment as PGZ1 and that with the option adjustment as PGZ2. The excess bond premium is obtained using these two expected returns separately.

3.1. Empirical Tests

We estimate the predictive regression over different return horizons: Monthly ($k = 1$), quarterly ($k = 3$), and annually ($k = 12$). For in-sample tests, we use the adjusted R^2 to compare the performance of different predictive regressions. For out-of-sample tests, we estimate the parameters of the predictive regression model recursively and use the out-of-sample R^2 to evaluate forecasting efficiency. Suppose that the sample period is from time 1 to T, and the out-of-sample forecast begins from time s. At any time t between s and T, we use the information up time t to estimate the coefficients, and then use the coefficients and the value of variables at time t to forecast corporate bond returns in the following k periods. Similarly, at time $t+1$, we use the data up to $t+1$ for the forecast and so forth, until $T-k$. We use the same recursive method to calculate the historical average, that is, historical mean returns are also updated each period. To be consistent with theory, we follow (Campbell and Thompson 2008) to set the regression coefficient to zero if it has a wrong sign and set the forecast to zero if the forecast of bond premium is negative.

To assess the out-of-sample performance, we calculate the following out-of-sample R^2 statistic (see Fama and French 1989; Campbell and Thompson 2008):

$$R_{OS}^2 = 1 - \frac{\sum_{t=s}^{T-k}\left(r_{t,k} - \hat{r}_{t,k}\right)^2}{\sum_{t=s}^{T-k}\left(r_{t,k} - \bar{r}_{t,k}\right)^2}, \quad (2)$$

where $r_{t,k}$ is the realized return between t and $t+k$, $\hat{r}_{t,k}$ is the out-of-sample forecast from the predictive regression, and $\bar{r}_{t,k}$ is the out-of-sample forecast based on the updated historical average, $\bar{r}_{t,k} = \frac{1}{t-k}\sum_{m=1}^{t-k} r_{t,k}$. R_{OS}^2 measures the improvement in mean-square-prediction errors (MSPE) for a predictive regression over the historical average forecast. A positive R_{OS}^2 implies the predictive regression forecast outperforms the historical mean forecast.

(Clark and West 2007) provide a one-sided test of the null hypothesis that expected squared prediction errors from the historical mean forecast and the predictive regression forecast are equal, against the alternative that the latter has lower squared prediction errors. To test the significance of out-of-sample R^2_{OS}, following (Clark and West 2007), we first compute the squared error difference,

$$\mu_{t,k} = (r_{t,k} - \bar{r}_{t,k})^2 - [(r_{t,k} - \hat{r}_{t,k})^2 - (\bar{r}_{t,k} - \hat{r}_{t,k})^2] \tag{3}$$

and then regress $\mu_{t,k}$ on a constant to obtain the t-statistics of its intercept. This statistic gives a p-value for the one-sided test under the standard normal distribution. We adjust standard errors by the method of (Hodrick 1992) to account for the effect of overlapping residuals when the forecast horizon is longer than one month.

In addition to individual forecasts, we employ the combination forecast as in (Rapach et al. 2010) to reduce the impacts of model uncertainty and instability in forecasting by individual predictors. Given L predictors, we have L out-of-sample forecasts, denoted as $r_{it,k}$, $i = 1, 2, \ldots, L$. The combination forecast at time t is the weighted average of L individual forecasts, $\hat{r}_{ct,k} = \sum_{i=1}^{L} \varpi_{it} r_{it,k}$, where ϖ_{it} is the weight for combining individual forecasts. In empirical investigation, we focus on the mean combination forecast.[2]

3.2. Asset Allocation

The return forecast provides important information for asset allocation. Different return forecasts will result in different portfolio choices, which give investors distinct risk and return trade-offs. An important question is whether the impact of using the predictive model in return forecasts is economically significant. Following (Marquering and Verbeek 2004; Welch and Goyal 2008; Campbell and Thompson 2008), we use the realized utility gain for a mean-variance investor as a measure of economic significance. This measure is calculated from the portfolio allocation based on either historical mean or the predictive regression forecast.

A mean-variance investor who forecasts the return with horizon k using a model i will decide at time t to allocate a proportion of the portfolio $w_{i,t} = \frac{1}{\gamma}(\frac{\hat{r}_{it,k}}{\hat{\sigma}^2_{t+1,k}})$ to risky bonds between t and $t+k$, where $\hat{\sigma}^2_{t+1,k}$ is the estimate of the variance of bond excess returns, γ is the risk aversion coefficient, and i = 1 or 0, represents the return forecast using the predictive model (1) and the historical mean (0), respectively. The risk aversion coefficient is set equal to five (see also Thornton and Valente 2012). We use the 10-year rolling window to estimate the variance of bond returns.[3]

Over the out-of-sample period, an investor using a model i to forecast returns with horizon k earns an average utility level of

$$\hat{v}_{i,k} = \hat{u}_{i,k} - \frac{1}{2}\gamma\hat{\sigma}^2_{i,k}, \tag{4}$$

where $\hat{u}_{i,k}$ and $\hat{\sigma}^2_{i,k}$, i = 1 and 0, are the sample mean and variance of returns of the portfolio formed by the excess return forecasts based on the predictive model (1) and the historical average (0), respectively. $\hat{v}_{1,k} - \hat{v}_{0,k}$ 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.

(Thornton and Valente 2012; Gargano et al. 2019; Sarno et al. 2016) suggest a joint asset allocation approach when studying the predictability of Treasury market returns. Using this approach, we examine the robustness of results by testing economic significance of multiple risky assets jointly. Suppose that there are N risky assets. The predicted return vector forecasted by model i is $\widehat{\Upsilon}_{it,k}$ where $i = 1, 0$ represents the forecast using the predictive regression and historical average, respectively. Given the return variance–covariance matrix at time t, $\widehat{\Omega}_{t,k}$, an investor will optimally allocate risky assets jointly by

$$\Pi_{i,t} = \frac{1}{\gamma}\widehat{\Omega}^{-1}_{t,k}\widehat{\Upsilon}_{it,k}, i = 1, 0. \tag{5}$$

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2 (Rapach et al. 2010) show that mean combination forecasts perform as well as more complicated weighting schemes.

3 Our results are not sensitive to the value of the risk aversion coefficient. Following the convention (see Campbell and Thompson 2008), the portfolio weight is constrained between 0% and 300%.

Once the optimal weight vector is obtained, we follow a similar process for the univariate risky asset to calculate the realized utility levels of the predictive and historical mean models, and assess the utility gain of the predictive regression by taking the difference of two utility levels.

4. Data

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

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

We merge the data from all sources. Month-end prices are used to calculate monthly returns. The monthly corporate bond return as of time t is computed as follows:[4]

$$R_t = \frac{(P_t + AI_t) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}} \tag{6}$$

where P_t is the price, AI_t is accrued interest, and C_t is the coupon payment, if any, in month *t*. We drop the Datastream data if returns are available from other sources. We choose transaction-based data when both LBFI and transaction-based data are available. The combined corporate bond return data run from January 1973 to December 2014. We exclude bonds with maturity less than one year and longer than 30 years, and select only straight bonds to avoid confounding effects of embedded options. However, we include the callable bonds when constructing the marketwide GZ spread. The final sample includes 1,069,794 monthly return observations for 39,377 bonds issued by 4549 firms.

We construct the credit spread variables using the procedure suggested by (Gilchrist and Zakrajsek 2012). Figure 1 plots the time series of GZ spreads, which resemble those reported by (Gilchrist and Zakrajsek 2012). These variables have the largest spike during 2007–2009, reflecting the impact of the financial crisis.

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[4] We use log returns so that long horizon returns can be easily calculated by the sum of monthly returns.

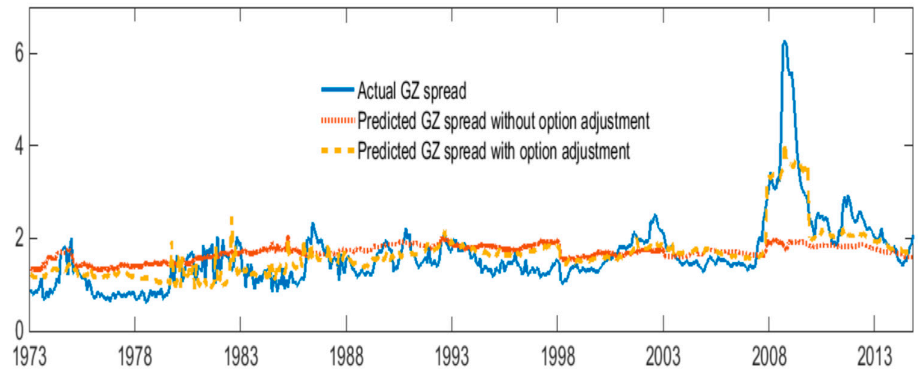

Figure 1. The Gilchrist and Zakrajsek (GZ) spreads and the excess bond premium. This graph plots the time series of GZ spreads, including the actual GZ spread, predicted GZ spread without option adjustment, and predicted GZ spread with option adjustment.

In addition to the GZ predictors, we use the following predictors in our empirical analysis:

a. Default spread, DFS: The difference between BAA- and AAA-rated corporate bond yields. The data are downloaded from Amit Goyal's webpage.
b. Issuer quality, IQ: Following (Greenwood and Hanson 2013), we calculate the fraction of nonfinancial corporate bond issuance in the last 12 months with a speculative grade,

$$IQ_t = \frac{\sum_{q=1}^{11} Junk_{t-q}}{\sum_{q=1}^{12} Invest_{t-q} + \sum_{q=1}^{11} Junk_{t-q}} \quad (7)$$

where $Junk_t$ and $Invest_t$ are the par values of issuance with a speculative and investment grade in month t, respectively. The data of monthly issues for the period 1973–1993 are from the Warga tape and after 1994, from the FISD.
c. Commercial paper spread, CPS: The difference between the one-month nonfinancial commercial paper rate and the one-month Treasury bill rate downloaded from the Federal Reserve.
d. Treasury bill rate, TB: The interest rate on a three-month Treasury bill (secondary market) from the Federal Reserve.
e. Term spread, TMS: The difference between the long-term yield and the Treasury bill rate taken from Amit Goyal's webpage.

5. Empirical Results

We run predictive regressions using bond portfolio returns as the dependent variable. Value-weighted portfolios are formed each month by rating and maturity. In each month, we sort all bonds independently into four rating portfolios: AAA/AA, A, BBB and junk bonds, and five duration portfolios based on the quintiles of bond duration distribution. In all, 20 portfolios are constructed at the intersection of ratings and duration (maturity).

Table 1 reports summary statistics of bond portfolios and predictive variables. Panel A shows mean and standard deviation of bond returns by rating and maturity. Both average return and volatility increase as the rating decreases. In addition, average returns and volatility are higher for long-maturity bonds. Panel B reports summary statistics of predictors in three categories: Conventional credit spreads, GZ spreads, and term structure variables, and Panel C shows correlations among predictors. Correlations are generally moderate except for those variables in the GZ family. Moderate correlations suggest that these predictors contain different information, which may complement each other.

Table 1. Summary statistics of corporate bond portfolios and the predictors. This table reports the summary statistics of corporate bond portfolios and the predictors used in the analysis. Panel (**A**) reports summary statistics of corporate bond portfolios, including rating portfolios, and short- and long-duration portfolios. In each month, we sort all bonds independently into four rating portfolios and five duration portfolios. In all, 20 duration portfolios are constructed at the intersection of rating and duration. Short (long) duration portfolio is the lowest (highest) quintile duration portfolio. The results of both excess return and duration-adjusted excess return are reported. The excess return is the return adjusted by the one-month risk-free interest rate, while the duration-adjusted excess return is the return adjusted by the return of duration-matched Treasury securities. Panel (**B**) reports summary statistics of predictors used in the analysis, including the default spread (DFS), the issuer quality index (IQ), the commercial paper spread (CPS), the actual GZ spread (AGZ), the predicted GZ spread without option adjustment (PGZ1), the predicted GZ spread with option adjustment (PGZ2), the excess bond premium excluding the effect of option adjustment on callable bonds (EBP), the three-month Treasury bill rate (TBL), and term spreads (TMS). Panel (**C**) reports the correlation among predictors.

Panel (A) Summary Statistics of Corporate Bond Portfolios					
		Total Excess Returns		**Credit-Spread Excess Returns**	
Rating	**Duration**	**Mean (%)**	**SD (%)**	**Mean (%)**	**SD (%)**
AAA/AA	All	0.21	1.41	0.11	1.42
	Short	0.13	0.71	0.07	0.72
	Long	0.31	2.36	0.17	2.36
A	All	0.26	1.62	0.16	1.62
	Short	0.18	0.92	0.12	0.93
	Long	0.36	2.55	0.22	2.53
BBB	All	0.33	1.71	0.22	1.70
	Short	0.26	1.24	0.20	1.25
	Long	0.45	2.74	0.30	2.72
Junk	All	0.48	2.10	0.38	2.10
	Short	0.33	2.60	0.26	2.60
	Long	0.78	3.03	0.64	3.01
All	All	0.32	1.55	0.22	1.55
	Short	0.22	1.12	0.16	1.12
	Long	0.47	2.38	0.33	2.36
Panel (B) Summary Statistics of Predictors					
Predictors		**Mean**	**SD**	ρ**(1)**	ρ**(12)**
Conventional default spread/index variables	DFS (%)	1.10	0.46	0.96	0.44
	IQ	−0.26	0.20	0.98	0.43
	CPS (%)	0.62	0.85	0.47	0.33
GZ-family variables	AGZ (%)	1.62	0.75	0.95	0.54
	PGZ1 (%)	1.69	0.16	0.95	0.69
	PGZ2 (%)	1.66	0.50	0.93	0.65
	EBP (%)	−0.07	0.68	0.94	0.48
Term structure variables	TBL (%)	5.02	3.40	0.99	0.85
	TMS (%)	2.11	1.50	0.95	0.48

Panel (C) Correlation among Predictors									
Predictors	**AGZ**	**PGZ1**	**PGZ2**	**EBP**	**DFS**	**IQ**	**CPS**	**TBL**	**TMS**
AGZ	1.00	0.50	0.84	0.98	0.43	−0.20	−0.15	−0.49	0.33
PGZ1		1.00	0.61	0.32	−0.05	−0.35	−0.11	−0.32	0.33
PGZ2			1.00	0.78	0.18	−0.28	−0.28	−0.64	0.43
EBP				1.00	0.49	−0.14	−0.14	−0.47	0.29
DFS					1.00	0.20	0.14	0.25	0.09
IQ						1.00	0.09	0.31	−0.17
CPS							1.00	0.51	−0.40
TBL								1.00	−0.64
TMS									1.00

5.1. In-Sample Regressions

We first run univariate regressions of excess returns of corporate bonds against each individual predictor. The dependent variable is the value-weighted excess return for each rating/duration portfolio. The predictors include three sets of variables: Conventional default-risk predictors, the GZ-family variables, and term structure variables. Tables 2–4 report the results of in-sample predictive regressions over monthly, quarterly, and yearly return horizons. Many predictors are significant in terms of *t*-statistics and have coefficients of predicted sign. We show the results for four rating portfolios: AAA/AA, A, BBB, and junk bonds, and the full portfolio including all bonds.[5] Results show that conventional default-risk indicators such as default spreads (DFS) and commercial paper spreads (CPS) have predictive power. The predictive power of both variables is higher for lower-rated bonds and increases as the return horizon lengthens. On the other hand, the issuer quality index (IQ) has predictive power only for the yearly return horizon.

Relative to the conventional credit spread predictors, the GZ variables have much higher predictive power. For the portfolio that includes all bonds, the GZ credit spread (AGZ) has an adjusted R^2 about twice as large as that for the default spread over the quarterly and annual horizons. The predictive power of the GZ variables is substantially higher for lower-grade bonds. Results show that these credit spread variables capture the default risk premium of bonds, which is more important for low-grade bonds.

When we decompose the GZ index into the predicted and unpredicted (the excess bond premium) components, we find that both have predictive power but the former has higher power than the latter. The predicted power of the credit spread components is not sensitive to the adjustment for the call option. In fact, the predicted GZ component (PGZ1) has slightly higher predictive power than the predicted component with an option adjustment (PGZ2). This finding suggests that the call option in bonds contain useful information for future returns.

Interestingly, the predictive power is highest when we use both the predicted credit spread component and the excess bond premium (PGZ1 + EBP) without the option adjustment as predictors. The bivariate regressions based on these two variables produce the largest in-sample R^2 among all rating portfolios over the annual horizon. One possible explanation for this finding is that the components of credit spreads contain differential information that captures different dimensions of return predictability and thus, including these two components increases the predictive power for corporate bond returns.

For term structure variables, we find that short rates have predictive power for corporate bond returns. Interest rates are closely related with business cycles, high when the economy is good and low when it is poor. The predictive power of interest rates increases as bond ratings decrease. The slope of term structure or the term spread (TMS) also has predictive power. When including both the level (TBL) and slope of the term structure (TMS) as predictors, the predictive power increases.

When further dividing the sample into different maturities, we find that conventional credit spread variables and GZ variables have higher predictive power for short-duration bonds. Short rates have higher predictive power for short-duration bonds than for long-duration bonds. Including both short rates and term spreads has higher predictive power for long-duration bonds. The results suggest that term spreads contain long-term information that is important for long-maturity bonds.

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5 We combine AAA/AA bonds to increase reliability of estimation as in some years the number of AAA observation is low. Our results are robust to separation of AAA from AA bonds (see Supplementary Materials posted online).

Table 2. In-sample predictive regressions (Monthly). This table reports the in-sample parameter estimates and adjusted R^2 values of predictive regressions for the monthly horizon. The excess return is used as the dependent variable. The predictors include three sets of variables: The conventional credit spread variables, the GZ variables, and term structure variables. The conventional credit spread variables include the default spread (DFS), the issuer quality index (IQ), and the commercial paper spread (CPS). The GZ-family credit spread variables include the actual GZ spread (AGZ), the predicted GZ spread without an option adjustment (PGZ1), the predicted GZ spread with an option adjustment (PGZ2), and the excess bond premium without an option adjustment on callable bonds (EBP). Term structure variables include the three-month Treasury bill rate (TBL) and the term spread (TMS). The t-values are calculated using the (Newey and West 1987) adjusted standard errors.

		Coefficients					t-Values					Adjusted R^2 Values				
	Predictors	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	DFS	0.17	0.47	0.53	0.67	0.45	1.37	3.34	3.38	3.79	3.29	0.17	1.99	2.04	2.60	1.93
	IQ	−0.10	0.23	0.04	0.30	0.14	−0.35	0.71	0.12	0.73	0.43	−0.18	−0.10	−0.20	−0.09	−0.16
	CPS	−0.17	−0.24	−0.30	−0.31	−0.26	−2.35	−3.03	−3.50	−3.15	−3.33	0.90	1.61	2.19	1.75	1.97
	AGZ	0.17	0.28	0.34	0.54	0.32	2.09	3.16	3.49	4.84	3.72	0.67	1.77	2.19	4.30	2.51
	PGZ1	1.22	1.26	1.27	1.85	1.37	3.34	3.07	2.79	3.58	3.44	1.99	1.66	1.35	2.31	2.12
	PGZ2	0.24	0.37	0.48	0.72	0.43	2.05	2.81	3.31	4.39	3.37	0.63	1.37	1.96	3.53	2.03
	EBP	0.14	0.26	0.34	0.52	0.30	1.62	2.78	3.28	4.43	3.32	0.32	1.33	1.92	3.61	1.97
	TBL	−0.04	−0.04	−0.08	−0.08	−0.06	−2.09	−2.37	−3.65	−3.45	−3.28	0.67	0.91	2.41	2.13	1.90
	TMS	0.13	0.19	0.25	0.26	0.21	3.41	4.39	5.45	4.82	5.06	1.89	3.38	5.25	4.11	4.50
Short-duration portfolios	DFS	0.17	0.36	0.56	0.69	0.47	2.68	5.14	5.82	4.65	5.60	1.22	4.84	6.17	3.96	5.71
	IQ	0.07	0.25	0.22	0.49	0.28	0.48	1.49	0.94	1.41	1.40	−0.15	0.24	−0.02	0.20	0.19
	CPS	−0.06	−0.09	−0.13	−0.24	−0.13	−1.78	−2.29	−2.42	−2.90	−2.82	0.43	0.84	0.96	1.46	1.37
	AGZ	0.07	0.20	0.36	0.39	0.27	1.80	4.44	5.83	4.12	5.08	0.45	3.62	6.20	3.11	4.74
	PGZ1	0.62	0.69	0.83	0.90	0.78	3.50	3.31	2.86	2.07	3.13	2.21	1.96	1.42	0.65	1.74
	PGZ2	0.11	0.25	0.42	0.49	0.34	1.86	3.78	4.61	3.59	4.36	0.49	2.59	3.91	2.33	3.49
	EBP	0.05	0.20	0.38	0.40	0.27	1.20	4.13	5.92	4.07	4.82	0.09	3.12	6.39	3.03	4.26
	TBL	−0.01	−0.02	−0.04	−0.05	−0.03	−0.84	−1.91	−2.67	−2.53	−2.49	−0.06	0.53	1.21	1.07	1.03
	TMS	0.06	0.09	0.14	0.18	0.12	3.07	4.36	4.81	3.94	4.58	1.88	3.51	4.10	2.62	3.71
Long-duration portfolios	DFS	0.15	0.46	0.72	0.85	0.61	0.67	1.98	2.92	3.15	2.74	−0.11	0.58	1.48	1.75	1.28
	IQ	−0.55	−0.16	0.09	0.42	−0.06	−1.09	−0.30	0.15	0.66	−0.11	0.04	−0.18	−0.20	−0.11	−0.20
	CPS	−0.30	−0.43	−0.48	−0.49	−0.44	−2.44	−3.37	−3.50	−3.28	−3.56	0.98	2.03	2.20	1.90	2.27
	AGZ	0.31	0.36	0.47	0.70	0.48	2.25	2.43	3.04	4.11	3.44	0.80	0.97	1.63	3.09	2.13
	PGZ1	1.82	2.01	1.58	2.78	2.07	2.88	2.99	2.20	3.54	3.21	1.44	1.56	0.76	2.26	1.83
	PGZ2	0.42	0.49	0.64	0.92	0.63	2.08	2.30	2.80	3.69	3.07	0.66	0.86	1.36	2.46	1.67
	EBP	0.28	0.31	0.47	0.66	0.46	1.89	1.99	2.88	3.68	3.13	0.52	0.59	1.44	2.46	1.73
	TBL	−0.09	−0.09	−0.10	−0.11	−0.10	−2.98	−2.89	−2.92	−2.92	−3.26	1.55	1.45	1.48	1.48	1.89
	TMS	0.24	0.33	0.34	0.38	0.33	3.72	4.73	4.58	4.69	5.05	2.43	3.90	3.64	3.83	4.48

Table 3. In-sample predictive regressions (Quarterly). This table reports the in-sample parameter estimates and adjusted R^2 values of predictive regressions for the quarterly horizon. The excess return is used as the dependent variable. The predictors include three sets of variables: The conventional credit spread variables, the GZ variables, and term structure variables. The conventional credit spread variables include the default spread (DFS), the issuer quality index (IQ), and the commercial paper spread (CPS). The GZ-family credit spread variables include the actual GZ spread (AGZ), the predicted GZ spread without an option adjustment (PGZ1), the predicted GZ spread with an option adjustment (PGZ2), and the excess bond premium without an option adjustment on callable bonds (EBP). Term structure variables include the three-month Treasury bill rate (TBL) and the term spread (TMS). The t-values are calculated using the (Newey and West 1987) adjusted standard errors.

		Coefficients					**t-Values**					**Adjusted R^2 Values**				
	Predictors	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	DFS	0.09	0.44	0.49	0.61	0.44	1.06	4.41	4.63	4.99	4.56	0.03	3.54	3.90	4.53	3.78
	IQ	−0.13	0.25	0.08	0.36	0.15	−0.66	1.07	0.30	1.24	0.66	−0.11	0.03	−0.18	0.11	−0.11
	CPS	−0.07	−0.12	−0.20	−0.19	−0.15	−1.49	−2.17	−3.33	−2.72	−2.67	0.24	0.73	1.97	1.25	1.20
	AGZ	0.18	0.31	0.41	0.56	0.39	3.44	5.03	6.18	7.48	6.46	2.12	4.63	6.92	9.89	7.52
	PGZ1	1.31	1.35	1.43	1.98	1.52	5.54	4.68	4.61	5.60	5.41	5.59	4.01	3.89	5.71	5.35
	PGZ2	0.24	0.34	0.50	0.66	0.45	3.10	3.71	5.17	5.93	5.02	1.69	2.48	4.88	6.38	4.61
	EBP	0.14	0.29	0.39	0.54	0.37	2.50	4.29	5.56	6.79	5.70	1.03	3.36	5.63	8.27	5.91
	TBL	−0.03	−0.04	−0.06	−0.07	−0.05	−2.71	−2.64	−4.51	−4.24	−3.79	1.25	1.17	3.70	3.27	2.59
	TMS	0.14	0.19	0.25	0.26	0.21	5.67	6.47	8.22	7.19	7.41	5.89	7.97	11.61	8.99	9.71
Short-duration portfolios	DFS	0.11	0.32	0.49	0.68	0.46	2.65	6.60	7.42	6.94	8.02	1.18	7.81	9.71	8.58	11.19
	IQ	0.07	0.25	0.20	0.53	0.28	0.67	2.10	1.23	2.23	1.94	−0.11	0.68	0.10	0.79	0.55
	CPS	0.01	−0.03	−0.08	−0.13	−0.06	0.24	−1.01	−2.00	−2.22	−1.74	−0.19	0.01	0.60	0.77	0.40
	AGZ	0.08	0.18	0.38	0.47	0.33	2.82	5.86	9.25	7.50	9.24	1.36	6.23	14.44	9.94	14.41
	PGZ1	0.63	0.68	1.00	0.97	0.87	5.04	4.71	5.07	3.24	4.96	4.65	4.05	4.70	1.87	4.49
	PGZ2	0.09	0.19	0.46	0.53	0.38	2.32	4.15	7.58	5.71	6.99	0.87	3.13	10.14	5.93	8.72
	EBP	0.06	0.17	0.38	0.50	0.34	1.90	5.23	8.67	7.65	9.00	0.51	5.00	12.90	10.30	13.77
	TBL	0.00	−0.01	−0.03	−0.04	−0.02	−0.13	−1.40	−3.59	−3.15	−2.86	−0.20	0.19	2.31	1.74	1.41
	TMS	0.05	0.08	0.15	0.18	0.12	4.04	5.67	7.51	6.00	6.66	4.74	7.18	10.10	6.44	8.30
Long-duration portfolios	DFS	0.02	0.45	0.69	0.88	0.53	0.14	2.96	4.32	4.91	3.67	−0.20	1.52	3.39	4.39	2.42
	IQ	−0.52	−0.08	0.16	0.46	−0.01	−1.68	−0.22	0.42	1.08	−0.03	0.36	−0.19	−0.16	0.04	−0.20
	CPS	−0.20	−0.26	−0.35	−0.31	−0.29	−2.62	−3.11	−3.92	−3.08	−3.59	1.15	1.69	2.77	1.66	2.31
	AGZ	0.32	0.45	0.54	0.78	0.53	3.77	4.74	5.42	6.99	5.84	2.57	4.10	5.37	8.72	6.21
	PGZ1	1.99	2.21	1.80	3.06	2.29	5.16	5.09	3.85	5.91	5.47	4.87	4.74	2.68	6.34	5.45
	PGZ2	0.44	0.53	0.64	0.92	0.64	3.52	3.84	4.35	5.61	4.76	2.22	2.67	3.46	5.73	4.14
	EBP	0.27	0.39	0.53	0.73	0.48	2.94	3.88	4.95	6.12	5.01	1.50	2.72	4.49	6.78	4.60
	TBL	−0.08	−0.08	−0.08	−0.09	−0.08	−4.35	−3.91	−3.84	−3.82	−4.29	3.44	2.77	2.67	2.63	3.34
	TMS	0.26	0.34	0.35	0.39	0.34	6.61	7.72	7.41	7.41	8.12	7.66	10.50	9.67	9.68	11.40

Table 4. In-sample predictive regressions (Yearly). This table reports the in-sample parameter estimates and adjusted R^2 values of predictive regressions for the annual horizon. The excess return is used as the dependent variable. The predictors include three sets of variables: The conventional credit spread variables, the GZ variables, and term structure variables. The conventional credit spread variables include the default spread (DFS), the issuer quality index (IQ), and the commercial paper spread (CPS). The GZ-family credit spread variables include the actual GZ spread (AGZ), the predicted GZ spread without an option adjustment (PGZ1), the predicted GZ spread with an option adjustment (PGZ2), and the excess bond premium without an option adjustment on callable bonds (EBP). Term structure variables include the three-month Treasury bill rate (TBL) and the term spread (TMS). The t-values are calculated using the (Newey and West 1987) adjusted standard errors.

		Coefficients					**t-Values**					**Adjusted R^2 Values**				
	Predictors	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	DFS	0.13	0.42	0.53	0.71	0.45	2.88	7.87	8.98	9.84	8.33	1.43	10.80	13.67	16.01	11.97
	IQ	−0.08	0.34	0.25	0.30	0.23	−0.76	2.63	1.72	1.65	1.72	−0.09	1.17	0.39	0.34	0.39
	CPS	−0.03	−0.06	−0.13	−0.13	−0.09	−1.34	−1.90	−3.75	−3.07	−2.83	0.16	0.52	2.53	1.65	1.38
	AGZ	0.15	0.30	0.43	0.62	0.38	5.18	9.03	12.17	15.05	11.52	4.90	13.86	22.71	31.04	20.81
	PGZ1	1.43	1.58	1.77	2.35	1.79	12.04	10.62	10.56	11.46	11.97	22.33	18.24	18.07	20.64	22.12
	PGZ2	0.21	0.36	0.54	0.77	0.47	5.03	7.12	10.14	12.05	9.57	4.63	9.03	16.88	22.35	15.30
	EBP	0.09	0.27	0.41	0.60	0.34	2.98	7.35	10.53	13.31	9.57	1.55	9.57	17.98	26.00	15.32
	TBL	−0.01	−0.02	−0.05	−0.06	−0.04	−2.46	−3.14	−5.83	−5.62	−4.72	0.99	1.74	6.15	5.74	4.06
	TMS	0.10	0.16	0.21	0.23	0.18	7.83	10.17	12.32	10.82	11.23	12.32	19.47	23.48	18.79	20.88
Short-duration portfolios	DFS	0.11	0.28	0.50	0.66	0.40	4.74	9.94	12.93	11.68	12.13	4.10	16.27	24.85	21.20	22.51
	IQ	0.06	0.28	0.26	0.24	0.22	1.06	4.11	2.53	1.62	2.56	0.02	3.08	1.07	0.32	1.10
	CPS	0.02	0.00	−0.05	−0.05	−0.02	1.38	0.19	−1.94	−1.29	−0.93	0.18	−0.19	0.55	0.13	−0.03
	AGZ	0.05	0.15	0.39	0.47	0.27	3.56	8.37	17.44	13.54	13.59	2.27	12.11	37.70	26.67	26.84
	PGZ1	0.64	0.74	1.12	1.34	0.97	9.88	8.98	9.23	7.53	9.70	16.17	13.71	14.38	10.00	15.66
	PGZ2	0.05	0.15	0.47	0.60	0.32	2.38	5.39	12.96	11.22	10.36	0.92	5.30	25.00	19.97	17.50
	EBP	0.03	0.14	0.40	0.48	0.27	1.70	7.08	16.45	12.77	12.29	0.37	8.93	34.97	24.44	23.04
	TBL	0.01	0.00	−0.02	−0.03	−0.01	1.76	0.09	−3.92	−3.78	−2.54	0.42	−0.20	2.77	2.57	1.07
	TMS	0.03	0.06	0.11	0.14	0.09	4.36	6.48	9.04	7.75	8.20	10.14	13.00	14.45	10.66	13.44
Long-duration portfolios	DFS	0.13	0.54	0.83	1.00	0.61	1.78	6.39	9.01	10.16	7.62	0.43	7.35	13.74	16.89	10.18
	IQ	−0.32	0.13	0.29	0.40	0.14	−1.83	0.63	1.25	1.59	0.70	0.47	−0.12	0.11	0.31	−0.10
	CPS	−0.13	−0.16	−0.21	−0.22	−0.18	−3.23	−3.40	−3.84	−3.63	−3.81	1.84	2.05	2.66	2.36	2.62
	AGZ	0.28	0.46	0.59	0.79	0.52	6.21	8.87	10.36	13.46	10.60	6.98	13.43	17.51	26.46	18.18
	PGZ1	2.25	2.62	2.52	3.46	2.68	11.62	11.55	9.50	12.54	12.34	21.11	20.91	15.11	23.78	23.20
	PGZ2	0.44	0.60	0.73	1.02	0.68	6.70	7.82	8.57	11.38	9.40	8.06	10.72	12.62	20.41	14.85
	EBP	0.20	0.39	0.55	0.74	0.45	4.10	6.96	8.89	11.44	8.52	3.06	8.65	13.47	20.59	12.52
	TBL	−0.06	−0.06	−0.07	−0.07	−0.06	−5.76	−5.15	−5.30	−5.18	−5.67	6.02	4.83	5.11	4.88	5.83
	TMS	0.22	0.30	0.33	0.37	0.30	10.69	13.24	12.47	13.07	13.65	18.35	27.38	24.49	26.74	28.13

Given that the GZ variables have greater predictive power than conventional credit spread variables, we next examine whether including the GZ and term structure variables can improve forecasting performance. Table 5 reports the in-sample R^2 for the multiple regressions that include both the GZ variables and term structure variables. The R^2 values are nearly twice as large as those using the GZ variables or term structure variables alone. For example, the regression that includes the two term structure variables and the two GZ variables (PGZ1 + EBP) generates a R^2 value of 41.30% for the portfolio including all bonds and 45.73% for junk bonds over the yearly horizon. The results show that including both GZ and term structure variables produces high predictive power for corporate bonds. The results for portfolios with different maturities show a similar pattern. Predictability is higher for short bonds over monthly and quarterly horizons, and higher for long bonds over the yearly horizon. Overall, the results suggest that corporate bond returns are predictable.

5.2. Out-Of-Sample Regressions

The results above show that the GZ variables perform well in the in-sample forecast. However, a good in-sample forecasting performance does not necessarily guarantee a good out-of-sample performance. The out-of-sample test provides a more stringent evaluation for the usefulness of a predictive model. In addition, it informs whether investors can use the predictive model to help them time the market and improve portfolio allocation decisions.

Panel A of Table 6 reports the out-of-sample forecasting results. Similar to in-sample regression results, the GZ variables perform much better than traditional default spread variables over both short and long forecast horizons. Regardless of which predictive models are used, credit spread variables have higher predictive power for low-grade bonds than for high-grade bonds, and return predictability is higher for the longer horizon (yearly). Moreover, including the predicted and unexpected GZ spread components outperforms the GZ spread variable (AGZ) itself, over all horizons. The advantage of using separate GZ spread components in the out-of-sample regression is even more apparent when the sample is divided into short- and long-term portfolios.

Term structure variables also have out-of-sample predictive power, and the predictive power of these variables is higher for lower-grade bonds. The out-of-sample R^2 for the model with short rates and term spreads is 13.86% over the yearly return horizon. When dividing the sample into short- and long-duration portfolios, the out-of-sample performance is better for long-duration bonds. Including both short rates and term spreads (TBL + TMS) produces an out-of-sample R^2 of 21% over the yearly horizon.

Table 5. In-sample R^2 of predictive regressions with GZ and term structure variables. This table reports the in-sample adjusted R^2 of predictive regressions using the GZ-family variables and term structure variables. The excess return is used as the dependent variable. The GZ family credit spread variables include the actual GZ spread (AGZ), the predicted GZ spread without an option adjustment (PGZ1), the predicted GZ spread with an option adjustment (PGZ2), and the excess bond premium without an option adjustment on callable bonds (EBP), while term structure variables include the three-month Treasury bill rate (TBL) and the term spread (TMS).

	Predictors	**Monthly (%)**					**Quarterly (%)**					**Yearly (%)**				
		AAA/AA	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	TBL + TMS + AGZ	1.90	4.04	5.68	6.12	5.26	6.73	11.08	15.01	15.17	14.30	15.62	31.00	39.15	43.28	36.72
	TBL + TMS + PGZ1	2.77	3.77	5.24	4.66	4.94	8.90	9.61	12.46	11.12	11.72	29.14	30.77	32.26	30.30	33.93
	TBL + TMS + PGZ2	1.78	3.59	5.28	5.20	4.68	6.24	9.00	12.96	11.68	11.45	15.48	26.43	33.37	35.09	31.53
	TBL + TMS + EBP	1.76	3.85	5.71	5.81	5.07	6.14	10.27	14.53	14.27	13.38	12.96	27.47	36.05	39.46	32.47
	TBL + TMS + PGZ1 + EBP	2.59	4.08	5.61	6.02	5.32	8.81	11.16	14.77	15.25	14.41	29.00	35.53	41.20	45.73	41.30
Short-duration portfolios	TBL + TMS + AGZ	0.48	1.71	2.00	4.12	2.33	2.27	5.80	7.21	10.40	8.28	7.27	19.66	25.79	35.03	25.18
	TBL + TMS + PGZ1	1.98	6.13	8.77	4.37	6.98	6.34	13.30	21.93	14.21	21.30	14.52	28.71	50.92	35.28	41.19
	TBL + TMS + PGZ2	3.19	4.14	4.33	2.51	4.10	8.32	9.34	11.77	6.69	10.14	26.35	24.18	22.71	16.06	23.94
	TBL + TMS + EBP	2.05	5.17	6.51	3.55	5.76	6.04	10.20	17.91	10.24	15.81	13.53	21.73	39.64	29.99	33.20
	TBL + TMS + PGZ1 + EBP	1.71	5.86	9.27	4.49	6.78	5.41	12.28	21.02	15.05	21.16	11.41	24.95	48.71	33.54	37.49
Long-duration portfolios	TBL + TMS + AGZ	3.02	6.09	9.12	4.30	6.79	8.46	13.26	21.29	14.88	21.47	26.43	32.20	51.56	35.31	42.63
	TBL + TMS + PGZ1	2.34	3.87	3.88	5.26	4.97	8.09	12.18	12.23	15.42	14.38	20.57	35.32	36.06	47.43	39.66
	TBL + TMS + PGZ2	2.75	4.14	3.42	4.48	4.75	9.44	12.08	9.99	12.41	13.20	30.25	38.26	31.27	40.02	40.35
	TBL + TMS + EBP	2.21	3.70	3.53	4.54	4.46	7.63	10.87	10.39	12.44	12.37	20.55	32.45	31.17	42.02	36.21
	TBL + TMS + PGZ1 + EBP	2.28	3.78	3.90	4.96	4.89	7.75	11.55	11.97	14.18	13.60	18.73	32.27	33.58	43.05	35.89

Panel B of Table 6 reports the out-of-sample forecasts that include different predictors. For each bond group and forecast horizon, we report the results of multiple regressions that include term structure variables and the excess bond premium (EBP), and the three mean combination forecasts. (Rapach et al. 2010) show that a combination of individual forecasts can provide more stable forecasts and track movements in the risk premium more reliably over time. Mean combinations 1, 2, and 3 use the mean of individual forecasts by the GZ predictors, the GZ and term structure variables (TBL and TMS) and all predictors, respectively.

The results at the top of Panel B include out-of-sample R^2 for different rating portfolios and the full portfolio that contains all bonds (ALL). Among the three combination forecasts, the second combination, which includes the GZ and term structure variables, provides the best performance. By contrast, the third combination forecast that includes all variables performs not as well as other combination forecasts. One reason is that some traditional credit spread variables such as commercial paper spread and issuer quality index are noisy. As such, including these variables (in combination 3) does not help improve the out-of-sample performance. This argument is consistent with the findings for the regression that includes only term structure and EBP in row 1 where we exclude traditional credit spread variables. Including only term structure variables and EBP fares quite well against the best combination forecast. Thus, when combining different variables in return forecasts, one needs to select appropriate predictors for combination in order to achieve the best result.

Corporate bond returns are more predictable over longer return horizons. This pattern holds for both short- and long-maturity bonds, but the incremental predictive power is higher for long-maturity bonds. The multiple regressions with term structure variables and EBP perform better for long-maturity bonds. On the other hand, combination forecasts 1 and 2 provide more stable forecasts across most rating and maturities.

Collectively, we find that corporate bond returns are predictable and the GZ credit spread variables contain important information for future bond returns. The out-of-sample R^2 values are much higher than those reported for stock return forecasts, which are typically less than 1% (see, for example, (Welch and Goyal 2008; Rapach et al. 2010). Moreover, there is evidence that the GZ credit spread variables have higher predictive power than any conventional credit spreads.

Table 6. Out-of-sample R^2 of predictive regressions. This table reports out-of-sample R^2_{OS} of predictive regressions. The predictors include three sets of variables: The conventional credit spread variables, the GZ-family credit spread variables, and the term structure variables. The conventional spread variables include the default spread (DFS), the issuer quality index (IQ), and the commercial paper spread (CPS). The GZ-family credit spread variables include the actual GZ spread (AGZ), the predicted GZ spread without an option adjustment (PGZ1), the predicted GZ spread with an option adjustment (PGZ2), and the excess bond premium without an option adjustment on callable bonds (EBP). Term structure variables include the three-month Treasury bill rate (TBL) and term spread (TMS). Panels (**A**,**B**) report the results of individual predictors and multiple predictors, respectively. Mean combinations 1, 2, and 3 use the mean of individual forecasts using the GZ family predictors, the GZ family predictors and term structure variables, and all predictors, respectively. We use the method of (Clark and West 2007) to test the significance of R^2_{OS}, and follow (Hodrick 1992) to adjust for standard errors when the forecast horizon is beyond one month. The signs [a], [b], and [c] denote the significance at 1%, 5%, and 10% levels, respectively.

		Panel (A) Forecasts Using Individual Predictors														
		Monthly (%)					Quarterly (%)					Yearly (%)				
	Predictors	AAA/AA	A	BBB	Junk	All	AAA/AA	A	BBB	Junk	All	AAA/AA	A	BBB	Junk	All
Rating portfolios	DFS	−0.56	0.46	0.50	1.86 [c]	0.48	−2.15	0.53	0.94	2.34	0.43	−10.34	0.70	5.35	8.50 [c]	1.69
	IQ	0.66	0.30	−0.02	−0.34	−0.34	−1.79	−0.58	−0.98	−1.14	−1.51	−8.03	−5.05	−4.74	−4.41	−6.36
	CPS	2.71 [a]	1.67 [a]	2.04 [a]	1.84 [a]	2.54 [a]	1.90	1.80 [c]	3.36	1.62	2.64	−0.03	−0.48	3.51	0.76	0.95
	AGZ	1.61 [a]	1.69 [a]	1.98 [a]	5.49 [a]	3.25 [b]	−3.45	−0.33	4.85 [a]	6.06 [a]	4.60 [a]	−21.53	2.69 [a]	21.38 [a]	29.40 [a]	17.37 [a]
	PGZ1	2.93 [a]	2.27 [a]	1.80 [a]	3.97 [a]	3.39 [a]	5.47 [a]	3.40 [a]	4.27 [a]	5.44 [a]	5.55 [a]	12.56 [a]	11.66 [a]	13.57 [a]	16.32 [a]	17.03 [a]
	PGZ2	0.89 [a]	1.61 [a]	2.99 [a]	5.73 [a]	3.90 [a]	−0.75	1.12 [a]	3.91 [a]	3.61 [a]	3.62 [a]	−13.94	−0.57	16.27 [a]	20.12 [a]	13.26 [a]
	EBP	1.25 [c]	1.38	1.83 [c]	4.76 [a]	2.92 [b]	−0.36	−0.74	3.51 [a]	3.13 [b]	2.74 [a]	−2.34	4.15 [c]	17.40 [a]	17.34 [a]	12.88 [a]
	PGZ1 + EBP	2.57 [a]	1.95 [a]	2.27 [a]	5.71 [a]	4.16 [a]	1.19 [c]	0.64 [a]	5.34 [a]	5.23 [a]	5.22 [a]	2.21 [a]	3.60 [a]	19.36 [a]	22.99 [a]	17.43 [a]
	TBL	1.31 [a]	1.21 [a]	2.78 [c]	2.58 [a]	2.57 [a]	1.94 [c]	0.89	4.46 [b]	2.78 [b]	3.00 [b]	−2.98	−2.43	4.01	1.37	0.79
	TBL + TMS	1.57 [a]	2.88 [a]	4.13 [a]	3.56 [a]	3.88 [a]	3.85 [a]	4.79 [a]	7.84 [a]	5.19 [a]	6.08 [a]	4.92 [b]	12.06 [a]	17.67 [a]	10.93 [a]	13.89 [a]
Short-term portfolios	DFS	−3.28	2.24 [b]	5.26 [b]	2.68 [c]	4.38 [b]	−6.50	1.97 [c]	6.96 [c]	6.86 [b]	9.47 [b]	−16.01	3.80	16.94 [c]	17.50 [b]	16.93 [c]
	IQ	−2.93	−0.19	−0.13	−0.11	−0.23	−5.70	−0.78	−0.38	−0.60	−0.83	−16.74	−7.31	−3.53	−3.97	−6.51
	CPS	2.16 [b]	1.32 [b]	0.83 [c]	−0.19	0.66 [b]	−0.51	0.32	0.75	0.01	0.63	−3.16	−2.70	−0.46	−0.61	−1.33
	AGZ	2.61 [b]	4.97 [b]	6.80 [b]	2.66 [b]	5.06 [b]	−0.78	0.02 [b]	13.10 [a]	5.49 [a]	13.95 [a]	−26.97	−4.80	11.01 [a]	12.89 [a]	9.09 [a]
	PGZ1	3.94 [a]	2.21 [a]	1.16 [a]	1.09 [b]	2.27 [a]	1.62 [a]	0.79 [a]	3.90 [a]	1.79 [b]	3.87 [a]	−2.82	−0.73	8.57 [a]	6.93 [a]	10.77 [a]
	PGZ2	0.39 [a]	3.62 [a]	4.55 [a]	2.78 [b]	5.17 [a]	−8.14	−1.22	5.76 [a]	6.52 [a]	7.43 [a]	−19.74	−13.78	8.49 [b]	15.69 [a]	10.91 [b]
	EBP	2.61 [c]	4.12 [b]	6.48 [b]	2.24 [c]	4.78 [b]	−8.08	−0.09	11.64 [b]	4.27 [b]	12.21 [a]	−13.79	−2.00	26.67 [b]	19.67 [a]	19.86 [b]
	PGZ1 + EBP	3.81 [a]	3.95 [a]	5.85 [a]	2.08 [b]	4.61 [a]	−6.28	−0.96	12.27 [a]	3.36 [b]	11.66 [a]	−20.08	−7.78	25.61 [a]	18.93 [a]	20.22 [a]
	TBL	−0.30	0.61 [b]	1.55 [a]	0.78 [b]	1.23 [a]	−1.25	−0.76	1.75 [b]	0.20	0.70	−4.57	−7.82	−5.51	−3.39	−5.83
	TBL + TMS	1.48 [a]	1.99 [a]	2.30 [a]	1.21 [a]	2.02 [a]	2.47 [a]	1.49 [a]	3.87 [a]	1.70 [a]	2.81 [a]	3.50 [a]	0.70 [a]	2.48 [b]	1.48 [c]	2.73 [b]
Long-term portfolios	DFS	0.15	0.38	0.31	1.23 [c]	0.55	−0.20	0.39	0.00	3.00 [c]	−0.06	−3.59	1.27	4.83 [c]	7.65 [b]	−1.10
	IQ	2.67	1.04	0.86	−1.85	−0.04	0.36	−1.11	−0.29	−3.84	−2.41	−4.96	−7.23	−4.50	−10.63	−8.72
	CPS	2.72 [a]	2.73 [a]	2.07 [a]	2.31 [a]	3.34 [a]	3.82 [c]	3.81 [c]	3.96 [c]	3.09 [a]	5.13 [b]	5.41	4.29	5.76	2.91	4.70
	AGZ	1.46 [b]	0.88	4.25 [b]	3.59 [a]	3.49 [b]	−0.19	1.89 [a]	3.90 [a]	5.65 [a]	4.77 [a]	−6.97	9.70 [a]	8.59 [a]	19.57 [a]	13.16 [a]
	PGZ1	1.90 [a]	2.31 [a]	3.21 [b]	3.34 [a]	3.28 [a]	4.47 [a]	5.25 [a]	1.84 [a]	6.43 [a]	6.38 [a]	13.89 [a]	16.32 [a]	7.44 [a]	19.05 [a]	17.98 [a]

	PGZ2	1.21 [a]	1.53 [a]	4.63 [a]	4.06 [a]	4.21 [a]	1.20 [b]	2.32 [a]	1.54 [a]	4.06 [a]	4.97 [a]	−5.60	7.79 [a]	6.14 [a]	19.98 [a]	14.95 [a]
	EBP	1.14 [c]	0.66	4.15 [b]	3.00 [a]	3.09 [a]	0.44 [b]	0.67 [c]	3.25 [a]	1.38 [b]	2.44 [a]	4.90 [c]	9.84 [a]	14.74 [a]	12.17 [a]	13.19 [a]
	PGZ1 + EBP	1.45 [a]	1.78 [a]	3.57 [b]	4.12 [a]	3.92 [a]	1.96 [a]	3.51 [a]	3.35 [a]	6.42 [a]	6.61 [a]	8.12 [a]	12.42 [a]	11.39 [a]	23.03 [a]	19.42 [a]
	TBL	2.65 [a]	2.14 [a]	2.43 [a]	1.76 [a]	2.82 [a]	5.47 [b]	3.73 [b]	3.61 [b]	2.17 [b]	4.62 [b]	8.52	5.65	5.07	1.35	5.33
	TBL + TMS	2.82 [a]	4.27 [a]	3.47 [a]	4.36 [a]	4.77 [a]	6.66 [a]	8.96 [a]	4.76 [a]	8.55 [a]	9.32 [a]	15.53 [a]	25.50 [a]	9.26 [a]	18.44 [a]	21.14 [a]
		Panel (B) Forecasts Using Multiple Predictors														
		Monthly (%)					**Quarterly (%)**					**Yearly (%)**				
	Predictors	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	Regression: TBL + TMS + EBP	1.14 [a]	2.49 [a]	3.39 [a]	5.64 [a]	4.16 [a]	1.37 [a]	4.65 [a]	9.02 [a]	5.96 [a]	7.53 [a]	0.63 [a]	20.02 [a]	34.15 [a]	28.54 [a]	27.61 [a]
	Mean Combination 1	3.13 [a]	2.73 [a]	2.82 [a]	5.91 [a]	4.50 [a]	3.38 [a]	3.19 [a]	6.35 [a]	6.71 [a]	7.01 [a]	7.32 [a]	12.88 [a]	24.85 [a]	27.17 [a]	24.30 [a]
	Mean Combination 2	3.13 [a]	3.01 [a]	3.54 [a]	4.96 [a]	4.56 [a]	5.10 [a]	4.82 [a]	7.98 [a]	7.50 [a]	8.46 [a]	13.03 [a]	17.92 [a]	28.25 [a]	27.69 [a]	27.64 [a]
	Mean Combination 3	2.74 [a]	2.70 [a]	3.25 [a]	4.04 [a]	3.89 [a]	5.03 [a]	4.65 [a]	7.10 [a]	6.32 [a]	7.29 [a]	12.17 [a]	15.03 [a]	22.47 [a]	20.86 [a]	21.48 [a]
Short-duration portfolios	Regression: TBL + TMS + EBP	2.68 [a]	5.09 [a]	7.27 [a]	1.98 [b]	4.56 [a]	−3.82	5.46 [a]	15.81 [a]	5.10 [a]	17.04 [a]	−9.79	14.63 [a]	39.54 [a]	27.01 [a]	35.81 [a]
	Mean Combination 1	5.32 [a]	5.40 [a]	6.06 [a]	2.48 [b]	5.31 [a]	0.48 [b]	3.98 [a]	11.86 [a]	5.18 [a]	12.76 [a]	−2.12	5.86 [b]	25.89 [a]	20.50 [a]	24.47 [a]
	Mean Combination 2	4.38 [a]	5.32 [a]	6.06 [a]	2.39 [b]	5.15 [a]	4.59 [a]	6.24 [a]	12.12 [a]	5.37 [a]	13.04 [a]	9.09 [a]	13.19 [b]	25.43 [a]	19.54 [a]	25.85
	Mean Combination 3	3.55 [a]	4.73 [a]	5.29 [a]	2.22 [b]	4.56 [a]	5.42 [a]	6.65 [a]	9.99 [a]	4.87 [a]	10.92 [a]	10.75 [a]	13.65 [b]	19.44 [a]	15.58 [a]	20.46 [a]
Long-duration portfolios	Regression: TBL + TMS + EBP	1.83 [a]	3.12 [a]	4.29 [a]	5.13 [a]	4.75 [a]	4.73 [a]	7.92 [a]	6.38 [a]	9.95 [a]	10.10 [a]	14.54 [a]	31.02 [a]	26.21 [a]	34.09 [a]	32.93 [a]
	Mean Combination 1	2.11 [a]	2.29 [a]	4.73 [a]	4.57 [a]	4.65 [a]	3.57 [a]	4.79 [a]	5.05 [a]	7.40 [a]	7.97 [a]	11.27 [a]	20.36 [a]	21.49 [a]	29.35 [a]	26.75 [a]
	Mean Combination 2	2.47 [a]	2.92 [a]	3.32 [a]	4.53 [a]	4.74 [a]	5.14 [a]	6.61 [a]	6.51 [a]	8.92 [a]	9.92 [a]	16.04 [a]	26.00 [a]	26.98 [a]	32.83 [a]	32.21 [a]
	Mean Combination 3	2.38 [a]	2.74 [a]	2.80 [a]	3.73 [a]	4.06 [a]	5.26 [a]	5.94 [a]	5.94 [a]	7.56 [a]	8.58 [a]	14.81 [a]	20.94 [a]	24.44 [a]	25.73 [a]	26.04 [a]

5.3. Economic Significance of Out-Of-Sample Forecasts

The preceding results show that the GZ spread and term structure variables can predict corporate bond returns. We next examine whether the magnitude of predicted returns is of economic significance and thus generates practical value to investors. We first assess economic significance based on single asset allocation, then extend the analysis to multiple assets, and finally account for transaction costs.

Table 7 reports the utility gains of predicted returns for a mean-variance investor who switches from the historical average forecast to the predictive regression forecast. To facilitate consistent comparison, returns are annualized for all investment horizons. Panel A shows the utility gains for individual predictors. The upper panel shows the results for rating portfolios and the lower two panels show the results for short- and long-term portfolios in different rating categories.

When we use default spreads and issuer quality as predictors, utility gains are often negative. Consistent with the out-of-sample forecast R^2_{OS}, these conventional bond predictors do not perform well. In contrast, the GZ variables consistently deliver solid utility gains. The utility gains from using the term structure variables are also positive but smaller than those obtained by the GZ predictors. The economic gains of term structure variables are greater for long-term bonds. These utility gains are also much larger than those reported by equity return studies. For example, (Rapach et al. 2010) report average annualized utility gains around 0.5% for stock return forecasts, suggesting that the predictability of corporate bond returns is more significant economically.

Panel B reports utility gains based on the regressions with multiple predictors. Results show that combination forecasts deliver more stable and larger utility gains, compared to the multiple regressions that include term structure variables and EBP directly. All utility gains generated from combination forecasts are positive and more stable than those of multiple regressions. Here, we see that a clear advantage of the combination method is its ability to produce more reliable and consistent forecasts, relative to individual or multiple regression forecasts. Combination 2 again produces the best results. Utility gains are higher for lower-grade bonds and long-maturity bonds. Overall, the predictability of corporate bond returns is of economic significance.

Table 7. Utility gains of predictive regressions. This table reports the annualized utility gains of predictive regressions. The excess return is used as the dependent variable. The predictors include three sets of variables: Conventional credit spread variables, the GZ variables, and term structure variables. Conventional credit spread variables include the default spread (DFS), the issuer quality index (IQ), and the commercial paper spread (CPS). The GZ-family credit spread variables include the actual GZ spread (AGZ), the predicted GZ spread without an option adjustment (PGZ1), the predicted GZ spread with an option adjustment (PGZ2), and the excess bond premium without an option adjustment on callable bonds (EBP). Term structure variables include the three-month Treasury bill rate (TBL) and term spread (TMS). Panel (**A**) reports the results of individual predictive regressions, and Panel (**B**) reports the results of forecasts using multiple predictors. Mean combinations 1, 2, and 3 use the mean of individual forecasts by the GZ predictors, the GZ predictors and term structure variables TBL and TMS, and all predictors, respectively.

		Panel (A) Individual Predictive Regression Forecasts														
		Monthly (%)					**Quarterly (%)**					**Yearly (%)**				
	Predictors	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	DFS	−1.02	−1.20	−1.23	−1.61	−1.96	−1.11	−1.25	−1.04	−1.57	−1.77	−1.18	−1.60	−1.62	−1.25	−2.31
	IQ	−1.42	−0.52	−0.94	−0.39	−1.23	−1.28	−0.51	−0.57	−0.79	−1.07	−0.98	−1.17	−1.19	−1.26	−1.26
	CPS	1.79	2.64	3.43	1.86	2.79	0.46	1.27	2.14	0.76	1.38	−0.05	0.11	1.02	0.24	0.30
	AGZ	0.57	1.51	2.11	1.76	1.38	0.67	1.60	2.41	1.95	1.51	0.73	1.40	1.99	1.88	1.21
	PGZ1	1.12	1.99	2.02	1.80	1.76	1.32	2.41	2.70	2.38	2.11	1.33	2.12	2.48	3.15	1.83
	PGZ2	1.80	2.34	3.04	3.19	2.42	1.83	2.53	3.27	3.12	2.69	1.93	2.54	3.16	3.27	2.37
	EBP	0.19	1.11	1.76	1.23	1.04	−0.40	0.77	1.36	0.75	0.51	−0.18	0.64	1.03	0.95	0.39
	PGZ1 + EBP	1.43	1.60	2.45	3.29	1.75	1.71	2.45	3.41	3.49	2.57	1.10	1.92	2.74	3.72	1.82
	TBL	0.85	1.93	3.20	1.98	1.87	0.57	1.18	2.63	1.33	1.45	−0.33	0.09	1.47	0.87	0.48
	TBL + TMS	0.20	1.56	2.86	2.20	1.45	0.31	1.51	2.58	1.78	1.09	0.14	1.53	2.32	1.56	1.00
Short-duration portfolios	DFS	−1.43	−1.79	−1.43	−1.76	−1.03	−0.83	−1.39	−1.27	−0.77	−0.61	−0.69	−0.92	−0.80	−0.14	−0.57
	IQ	−0.72	−0.60	−0.49	−0.52	−0.61	−0.58	−0.51	−0.29	−0.73	−0.56	−0.58	−0.87	−0.74	−1.15	−0.88
	CPS	0.70	0.96	0.84	0.25	0.81	−0.02	0.28	0.24	0.12	0.32	−0.07	−0.12	0.11	−0.13	−0.03
	AGZ	0.12	0.42	1.35	−0.12	1.27	0.11	0.43	1.30	−0.30	1.12	0.11	0.26	0.88	0.61	0.60
	PGZ1	0.40	0.50	0.82	0.67	0.85	0.49	0.62	1.13	0.21	0.93	0.43	0.52	1.08	0.32	0.59
	PGZ2	0.68	0.86	1.67	−0.32	1.41	0.74	1.00	1.67	0.31	1.52	0.74	0.68	1.47	0.70	0.89
	EBP	−0.05	0.18	1.53	−0.33	1.26	−0.27	0.06	1.11	−0.36	0.85	−0.28	−0.27	0.66	0.15	0.06
	PGZ1 + EBP	0.35	0.49	1.64	0.96	1.63	0.34	0.62	1.65	−0.83	1.28	0.24	0.62	1.30	0.47	0.74
	TBL	0.11	0.55	1.34	0.36	1.07	−0.02	0.35	1.06	0.02	0.76	−0.04	−0.24	0.17	−0.30	0.07
	TBL + TMS	−0.10	−0.13	1.02	1.90	0.79	−0.37	−0.30	0.99	2.01	0.46	−0.50	−0.78	0.15	0.20	−0.33
Long-duration portfolios	DFS	−0.82	−1.32	−1.45	−0.90	−1.34	−0.61	−0.94	−1.43	−1.12	−1.57	−0.80	−0.77	−1.07	−1.38	−1.63
	IQ	−1.87	−1.68	−0.87	−2.21	−2.20	−1.65	−1.54	−0.86	−2.23	−1.78	−0.94	−1.40	−0.93	−2.29	−1.33
	CPS	2.57	2.44	3.16	3.19	4.07	1.27	1.15	1.81	1.62	2.40	0.48	0.39	0.84	0.80	0.74
	AGZ	1.56	1.06	2.30	2.32	1.80	1.43	1.86	2.34	2.64	2.42	0.75	1.42	1.93	1.60	1.68

	PGZ1	1.40	2.10	1.28	2.98	2.89	1.82	2.53	1.84	3.68	3.34	2.25	3.18	2.69	3.09	3.23
	PGZ2	2.07	2.77	2.49	4.61	3.48	1.88	2.58	2.27	4.10	3.75	1.78	2.58	2.69	3.80	3.65
	EBP	0.93	0.50	1.92	1.74	1.44	0.66	0.32	1.74	0.39	1.02	0.40	0.61	1.29	0.27	0.78
	PGZ1 + EBP	1.73	1.99	2.44	4.45	2.81	2.12	3.06	2.98	4.04	3.75	2.14	2.89	3.51	3.36	3.27
	TBL	1.98	1.69	2.38	2.51	2.17	1.58	1.12	1.35	1.73	2.04	0.69	0.34	0.48	0.95	0.75
	TBL + TMS	1.88	3.32	2.88	3.30	2.11	2.32	3.58	2.71	3.35	2.49	2.15	3.67	3.22	3.35	2.81
		Panel (B) Forecasts Using Multiple Predictors														
		Monthly (%)					**Quarterly (%)**					**Yearly (%)**				
	Predictors	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	Regression: TBL + TMS + EBP	0.24	1.10	2.58	2.14	1.14	0.45	1.51	2.42	1.22	0.73	−0.25	1.12	1.77	1.33	0.39
	Mean Combination 1	1.79	2.44	2.92	2.99	2.34	1.74	2.57	3.22	2.79	2.35	1.70	2.33	2.87	3.09	2.07
	Mean Combination 2	1.86	2.67	3.50	3.26	2.63	1.69	2.75	3.53	2.84	2.65	1.64	2.56	3.21	3.33	2.29
	Mean Combination 3	1.30	2.14	3.21	2.34	2.33	1.17	2.13	2.89	2.02	2.20	1.01	1.73	2.41	2.28	1.67
Short-duration portfolios	Regression: TBL + TMS + EBP	−0.15	−0.11	1.03	1.79	0.72	−0.65	−0.67	0.58	1.17	0.45	−0.70	−0.82	0.33	0.63	−0.22
	Mean Combination 1	0.59	0.79	1.68	0.07	1.51	0.56	0.88	1.69	0.24	1.46	0.51	0.68	1.35	0.51	0.86
	Mean Combination 2	0.81	0.96	1.75	0.51	1.62	0.68	0.98	1.74	0.21	1.54	0.66	0.73	1.43	0.50	0.88
	Mean Combination 3	0.56	0.88	1.46	0.31	1.45	0.48	0.88	1.43	0.30	1.34	0.43	0.62	0.99	0.47	0.64
Long-duration portfolios	Regression: TBL + TMS + EBP	1.80	2.74	1.68	3.77	2.32	1.95	2.83	2.59	2.57	2.52	1.98	3.24	3.05	2.25	2.11
	Mean Combination 1	1.94	1.82	2.34	3.68	2.93	2.06	2.20	2.67	3.95	3.52	1.99	2.66	2.91	3.58	3.41
	Mean Combination 2	2.29	2.43	2.98	3.97	3.41	2.37	2.59	2.79	4.16	3.80	2.31	3.10	2.76	3.87	3.58
	Mean Combination 3	2.05	2.00	2.77	2.99	2.89	1.84	2.10	2.55	2.90	3.03	1.59	2.10	2.59	2.48	2.52

5.4. Diversification among Risky Assets and Trading Costs

The preceding tests on the economic significance of return forecasts are performed separately for each risky bond portfolio. This method however ignores diversification among different risky assets. To examine the robustness of results, we next carry out the asset allocation jointly for bonds with different ratings and maturities.

Panel A of Table 8 reports utility gains for different rating portfolios. Utility gains remain significant under the joint asset allocation. Most combination forecasts generate annualized utility gains greater than 2%. Mean combination forecast 2 again delivers the largest utility gain. The results continue to show that traditional credit spread variables do not help improve bond return forecasts once GZ credit spread predictors are used. Long-term portfolios have higher utility gains than short-term portfolios. The utility gains of long-term portfolios are mostly above 3%, while they are around 2% for short-term portfolios. The results show that it is more beneficial to use the predictive model for long-term bonds.

The above analysis does not consider the transaction cost associated with asset allocation and rebalancing. The gains of using return forecasts of the predictive models may be overstated if the forecast of predictive regressions involves high turnover and transaction costs. To address this concern, we next calculate the utility gains net of transaction costs. We first subtract the transaction cost from portfolio returns and then recalculate the utility gains or certainty equivalent returns.

Panel B of Table 8 reports the utility gains net of transaction costs. Following (Edwards et al. 2007), we use 0.25% as the transaction cost of investment-grade bonds and 0.35% as the transaction cost of speculative-grade bonds. The results continue to show that the predictability of corporate bond returns by GZ predictors is of economic significance. Mean combination 2 still has the best performance, and the utility gain is more significant for the long-term portfolio than for the short-term portfolio. The predictive model generates significant economic gains that are robust to transaction costs.

5.5. Predictability of the Credit Spread Component of Corporate Bond Returns

The excess return of corporate bond returns contains two components: The credit spread component (default-related) and the term (interest rate) component. Specifically, we can decompose the excess return of corporate bonds as follows:

$$r_t = tr_t - r_{f,t} = (tr_t - r_{m,t}) + (r_{m,t} - r_{f,t}) \tag{8}$$

where tr_t is the raw return of corporate bond, $r_{m,t}$ is the return of Treasury security with the same maturity, and $r_{f,t}$ is one-month risk-free rate. The term $tr_t - r_{m,t}$ measures the credit spread component of corporate bonds and $r_{m,t} - r_{f,t}$ measures the term component of corporate bonds.

Table 8. Economic significance accounting for diversification among assets and trading costs. This table reports utility gains that account for multiple asset allocations (Panel A) and transaction costs Panel (**B**). In Panel (**A**), we use the four rating portfolios (AAA/AA, A, BBB, and Junk) with different duration groups jointly to calculate the utility gains. In Panel B, we use 35 bps as the transaction cost for junk bonds and 25 bps for investment-grade bonds. The forecast horizon is yearly. The predictors include three sets of variables: Conventional credit spread variables, the GZ variables, and term structure variables. Conventional credit spread variables include the default spread (DFS), the issuer quality index (IQ), and the commercial paper spread (CPS). The GZ variables include the actual GZ spread (AGZ), the predicted GZ spread without an option adjustment (PGZ1), the predicted GZ spread with an option adjustment (PGZ2), and the excess bond premium without an option adjustment on callable bonds (EBP). Term structure variables include the three-month Treasury bill rate (TBL) and term spread (TMS). Mean combinations 1, 2, and 3 use the mean of individual forecasts by the GZ predictors, the GZ predictors and term structure variables TBL and TMS, and all predictors, respectively.

		Panel (A) Utility Gains of Joint Asset Allocation														
		Monthly (%) Maturity Portfolios					Quarterly (%) Maturity Portfolios					Yearly (%) Maturity Portfolios				
	Predictors	Short	2	3	4	Long	All	Short	2	3	4	Long	All	Short	2	3
	Regression: TBL + TMS + EBP	2.35	0.78	2.54	2.85	0.49	1.00	3.11	0.18	1.65	3.01	1.15	0.80	1.73	1.74	0.36
	Mean Combination 1	2.09	0.83	3.03	1.43	3.15	2.87	2.56	0.96	2.98	2.14	3.21	2.22	2.61	2.12	2.22
	Mean Combination 2	2.37	1.30	3.58	1.99	3.85	3.52	2.86	1.08	3.19	2.69	3.71	2.27	2.78	2.27	2.35
	Mean Combination 3	1.61	1.12	2.73	1.78	3.34	2.86	2.06	0.97	2.81	2.70	3.00	1.71	2.17	1.21	1.72
		Panel (B) Utility Gains Net of Transaction Costs														
		Monthly (%)					**Quarterly (%)**					**Yearly (%)**				
	Predictors	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	Regression: TBL + TMS + EBP	−0.26	0.26	1.40	1.88	0.35	0.17	1.11	2.01	0.86	0.37	−0.29	1.04	1.68	1.24	0.31
	Mean Combination 1	2.50	3.08	3.38	4.14	3.21	1.97	2.77	3.42	3.12	2.71	1.77	2.39	2.92	3.16	2.15
	Mean Combination 2	2.65	3.43	4.12	4.68	3.64	1.94	3.00	3.81	3.35	3.06	1.72	2.63	3.26	3.41	2.39
	Mean Combination 3	1.96	2.89	3.82	3.58	3.18	1.36	2.31	3.11	2.29	2.52	1.07	1.78	2.46	2.34	1.74
Short-term portfolios	Regression: TBL + TMS + EBP	−1.04	−1.95	−0.54	0.72	−0.70	−1.16	−1.45	−0.04	0.74	−0.19	−0.85	−1.02	0.21	0.57	−0.37
	Mean Combination 1	1.86	1.56	2.63	0.30	2.29	0.95	1.10	1.90	0.31	1.70	0.60	0.73	1.45	0.53	0.93
	Mean Combination 2	2.43	2.08	2.84	0.62	2.55	1.22	1.30	2.03	0.43	1.85	0.78	0.80	1.53	0.51	0.95
	Mean Combination 3	1.81	1.84	2.40	0.43	2.26	0.83	1.15	1.65	0.38	1.59	0.51	0.67	1.08	0.48	0.69
Long-term portfolios	Regression: TBL + TMS + EBP	−0.35	0.96	−0.28	2.90	0.74	1.18	2.28	1.97	2.15	1.94	1.78	3.01	2.90	2.12	1.99
	Mean Combination 1	0.90	1.24	1.74	3.89	2.89	1.68	2.01	2.52	3.96	3.48	1.93	2.61	2.87	3.62	3.41
	Mean Combination 2	1.19	1.88	2.32	4.28	3.39	1.95	2.39	2.65	4.21	3.76	2.24	3.05	2.72	3.90	3.58
	Mean Combination 3	1.10	1.50	2.27	3.22	2.82	1.52	1.91	2.56	2.95	2.96	1.54	2.07	2.55	2.49	2.51

It is useful to investigate the predictability of the credit spread component of corporate bond excess returns for several reasons. First, investigating the predictability of different bond return components sheds light on the sources of return predictability. Second, while excess corporate bond returns as a whole are predictable, it is unclear which component of returns is predictable. The literature has shown that government bond returns are predictable. The predictability for the bond return in excess of the T-bill rate may simply reflect the predictability of the term component associated with the Treasury bond rate. If so, our finding for the predictability of corporate bond returns is spurious. Third, the credit spread return is the most important component of corporate bond returns, which makes these bonds different from government bonds. It is therefore important to examine whether the credit spread component is predictable in order to firmly establish the predictability of corporate bond returns. Fourth, the credit spread component behaves differently from the term component and varies across bonds of different quality (see Fama and French 1989). The credit spread component is expected to be more important for low-grade bonds than for high-grade bonds. Analyzing the credit spread return component thus provides deeper insight into predictability of bonds with different quality.

Panel A of Table 9 reports results of different predictive regressions. For brevity, we focus on the results for the annual return horizon as shorter investment horizons give similar results. We calculate the credit spread component for each bond and form the portfolios using the same procedure as described earlier. Table 9 shows that the credit spread component of excess corporate bond returns is predictable both in and out of sample. Thus, the predictability of corporate bond return is not due to the predictability of the interest rate component.

For in-sample regressions, the R^2 of credit spread component returns is comparable to that for the excess return (see Tables 2–4). Again, the GZ variables have the highest predictive power for the credit spread component of corporate bond returns. The level of short-term interest rates and the slope of term structure (TMS) also have predictive power for the credit spread component. Both the level and slope of term structure are linked to business cycles (see, for example, Longstaff and Schwartz 1995; Duffee 1998). This explains why term structure variables have explanatory power for credit spread returns. As expected, default spreads have higher predictive power for credit spread returns, given that the latter is associated with default risk. Default spreads are countercyclical, high (low) when the economy is poor (good). Default spreads hence capture bond return variations due to changes in economic conditions.

Table 9. Prediction of credit spread component returns. This table reports the results of predictive regression using the duration-adjusted excess returns as the dependent variable. The forecast horizon is yearly. The predictors include three sets of variables: Conventional credit spread variables, the GZ-family credit spread variables, and term structure variables. Conventional credit spread variables include the default spread (DFS), the issuer quality index (IQ), and the commercial paper spread (CPS). The GZ-family credit spread variables include the actual GZ spread (AGZ), the predicted GZ spread without an option adjustment (PGZ1), the predicted GZ spread with an option adjustment (PGZ2), and the excess bond premium without an option adjustment on callable bonds (EBP). Term structure variables include the three-month Treasury bill rate (TBL) and term spread (TMS). Panels (**A**,**B**) report the results of individual predictors and multiple predictors, respectively. Mean combinations 1, 2, and 3 use the mean of individual forecasts by the GZ predictors, the GZ predictors and term structure variables, and all predictors, respectively. We use the method of (Clark and West 2007) to test the significance of R^2_{OS}, and follow (Hodrick 1992) to adjust for standard errors when the forecast horizon is beyond one month. The signs ^{a}, ^{b}, and ^{c} denote the significance at 1%, 5%, and 10% levels, respectively.

		Panel (A) Individual Predictive Regression Forecasts														
		In-Sample Adjusted R^2 (%)					**Out-Of-Sample R^2 (%)**					**Annualized Utility Gains (%)**				
	Predictor	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	DFS	0.71	9.64	13.09	15.28	11.02	1.50	6.69	9.86 ^{c}	8.16 ^{c}	6.17	−0.25	0.34	0.10	−0.67	−0.20
	IQ	−0.04	1.20	0.45	0.33	0.40	0.14	−2.03	−2.41	−2.37	−3.35	−0.43	−0.27	−0.57	−0.69	−0.80
	CPS	−0.01	0.31	2.06	1.37	1.06	3.02	0.41	2.70	0.46	0.88	−0.05	−0.10	0.27	−0.01	0.18
	AGZ	4.35	13.36	22.02	31.27	20.58	−18.35	2.83 ^{a}	20.14 ^{a}	28.04 ^{a}	17.15 ^{a}	0.19	1.10	1.76	1.59	2.04
	PGZ1	21.53	17.62	17.31	20.12	21.62	11.03 ^{a}	10.11 ^{a}	12.03 ^{a}	14.80 ^{a}	15.28 ^{a}	1.53	2.52	2.22	2.96	2.87
	PGZ2	4.28	8.68	16.26	22.58	15.15	−16.58	−5.27	11.41 ^{a}	17.17 ^{a}	8.82 ^{a}	0.85	1.58	2.30	3.42	3.11
	EBP	1.25	9.24	17.54	26.43	15.24	3.47 ^{c}	4.63 ^{c}	16.73 ^{a}	15.93 ^{a}	12.80 ^{a}	0.13	0.65	1.15	0.67	1.24
	PGZ1 + EBP	21.47	20.73	26.31	35.32	28.03	2.24 ^{a}	−0.17	15.21 ^{a}	19.17 ^{a}	13.06 ^{a}	1.22	1.86	2.50	3.48	2.66
	TBL	0.65	1.37	5.21	5.33	3.51	1.85	−2.63	2.40	0.47	−0.43	−0.23	−0.55	0.24	0.29	0.19
	TBL + TMS	6.76	13.88	18.14	14.79	15.36	5.85 ^{b}	7.36 ^{a}	11.78 ^{b}	6.76 ^{b}	8.44 ^{a}	0.36	1.84	2.18	1.55	1.75
Short-term portfolios	DFS	2.43	13.41	23.16	19.86	20.29	−3.22	6.14	14.90 ^{c}	16.13 ^{c}	15.02	−0.87	−1.16	−0.84	0.04	−1.04
	IQ	−0.14	2.59	0.86	0.25	0.85	−6.32	−1.71	−1.65	−1.72	−3.22	−0.79	−0.28	−0.02	−0.35	−0.42
	CPS	−0.05	−0.20	0.61	0.17	0.06	0.15	−2.86	−0.47	−0.58	−1.42	−0.11	−0.15	0.05	−0.15	−0.07
	AGZ	3.51	13.72	40.25	28.06	29.70	−26.99	−1.24	35.19 ^{a}	25.84 ^{a}	29.96 ^{a}	0.35	0.74	1.52	0.70	1.02
	PGZ1	18.74	15.40	15.01	10.27	16.81	3.41 ^{a}	1.75 ^{a}	8.67 ^{a}	7.96 ^{a}	11.28 ^{a}	0.34	0.75	1.54	0.81	1.28
	PGZ2	2.04	6.89	27.51	21.56	20.31	−17.94	−11.72	9.81 ^{b}	15.68 ^{a}	13.72 ^{b}	0.79	1.21	1.94	1.03	1.38
	EBP	0.94	10.05	37.42	25.79	25.59	−0.26	4.42	26.99 ^{b}	20.36 ^{a}	22.98 ^{b}	−0.07	0.29	1.16	0.14	0.57
	PGZ1 + EBP	18.71	19.39	41.42	28.48	32.35	−10.29	−5.53	25.23 ^{a}	19.19 ^{a}	21.43 ^{a}	0.10	0.73	1.99	0.61	1.45
	TBL	−0.10	−0.10	3.49	3.08	1.82	−4.14	−8.10	−5.01	−2.97	−5.11	−0.32	−0.67	−0.37	−0.25	−0.09
	TBL + TMS	4.28	7.75	11.20	8.62	9.52	4.60 ^{b}	−1.94	−0.20	0.01	−0.16	−0.72	−0.53	0.33	0.73	0.21
Long-term portfolios	DFS	0.05	6.67	13.20	16.47	9.54	4.06	7.27 ^{c}	10.21 ^{b}	7.88 ^{b}	4.31	−0.11	0.27	0.23	−0.56	−0.61
	IQ	0.47	−0.09	0.21	0.38	−0.06	2.66	−0.47	−2.50	−7.90	−4.99	−0.30	−0.64	−0.65	−1.47	−0.91
	CPS	1.06	1.42	2.01	1.85	1.91	6.71	5.16	4.47	2.08	3.75	0.23	0.17	0.48	0.37	0.30

	AGZ	5.11	11.92	15.71	25.35	16.55	−8.11	8.72 [a]	6.05 [a]	22.42 [a]	11.63 [a]	0.26	0.35	1.42	1.20	0.92
	PGZ1	19.21	19.78	13.88	23.25	22.26	12.31 [a]	14.12 [a]	4.91 [a]	17.41 [a]	15.87 [a]	1.35	1.75	1.55	2.61	2.88
	PGZ2	6.28	9.45	11.03	19.36	13.41	−10.15	2.22 [a]	−2.00	15.22 [a]	8.57 [a]	0.28	0.53	1.22	2.93	1.88
	EBP	1.90	7.54	12.05	19.69	11.25	7.68 [a]	8.51 [a]	14.84 [a]	9.57 [a]	12.22 [a]	0.42	−0.22	1.31	0.74	0.79
	PGZ1 + EBP	19.05	21.62	19.57	32.49	25.95	6.80 [a]	7.44 [a]	6.32 [a]	17.94 [a]	14.10 [a]	1.11	1.21	2.02	2.86	2.61
	TBL	4.07	3.42	3.67	3.81	4.28	9.23	5.25	2.98	−0.17	3.27	0.39	0.05	0.24	0.33	0.03
	TBL + TMS	12.03	21.62	19.49	22.29	22.28	11.50 [a]	19.64 [a]	3.05 [a]	13.23 [a]	15.14 [a]	1.57	2.68	2.61	2.91	2.69
		Panel (B) Forecasts Using Multiple Predictors														
		In-Sample Adjusted R^2 (%)					**Out-Of-Sample R^2 Square (%)**					**Annualized Utility Gain (%)**				
	Predictors	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolios	TBL + TMS + EBP	7.31	21.89	30.93	36.23	27.29	3.[a]	13.94 [a]	26.94 [a]	22.49 [a]	21.09 [a]	0.41	1.69	2.04	1.12	1.60
	Combination 1						5.14 [a]	8.87 [a]	20.58 [a]	23.83 [a]	20.08 [a]	1.06	1.95	2.42	3.24	3.08
	Combination 2						8.90 [a]	12.02 [a]	22.34 [a]	23.44 [a]	21.65 [a]	0.94	1.93	2.49	3.26	3.08
	Combination 3						9.89 [b]	10.95 [b]	18.12 [a]	17.66 [a]	17.15 [a]	0.47	1.20	1.73	2.27	2.24
Short-term portfolios	TBL + TMS + EBP	5.84	19.71	46.81	32.14	34.82	−4.06	11.36 [a]	35.15 [a]	24.53 [a]	31.61 [a]	−0.79	−0.46	0.89	0.71	0.35
	Combination 1						2.47 [a]	6.53 [c]	25.19 [a]	20.75 [a]	24.99 [a]	0.67	1.14	1.81	0.73	1.23
	Combination 2						8.68 [a]	10.80 [b]	23.47 [a]	19.01 [a]	24.31 [a]	0.74	1.15	1.75	0.81	1.23
	Combination 3						10.38 [b]	11.24 [c]	17.68 [b]	14.92 [a]	18.79 [a]	0.55	0.82	1.37	0.72	0.92
Long-term portfolios	TBL + TMS + EBP	12.15	26.28	28.23	38.72	29.83	11.77 [b]	23.23 [a]	20.08 [a]	26.82 [a]	25.65 [a]	1.65	2.31	2.77	1.86	2.30
	Combination 1						7.82 [a]	15.62 [a]	15.78 [a]	25.11 [a]	21.62 [a]	1.13	1.35	1.94	2.56	2.42
	Combination 2						10.95 [a]	19.64 [a]	19.70 [a]	27.68 [a]	25.43 [a]	1.36	1.70	2.40	2.70	2.61
	Combination 3						11.53 [a]	16.91 [a]	19.13 [a]	21.98 [a]	21.04 [a]	1.03	1.06	1.89	2.29	1.87

The out-of-sample results convey a similar message that the credit spread component of bond returns is predictable. The R^2 of out-of-sample regressions is quite comparable to that of the excess return in Table 6. The results cast doubt that interest rates are the driver for corporate bond return predictability. The GZ variables again deliver the highest out-of-sample R^2 values. The predictive power of the GZ variables apparently derives from their ability to predict the credit risk premium of bonds.

Across ratings, credit spread returns are more predictable for lower-grade bonds whereas across maturities, returns are more predictable for short-term bonds. The combination of the two components of the GZ spread variables, PGZ1 + EBP, delivers the best performance in sample. However, for out-of-sample forecasts, the whole GZ spread (AGZ) at times performs better than its components.

Panel B of Table 9 reports the results of multiple regression and combination forecasts. The multiple regression forecasts using term structure variables and excess bond premium (EBP) produce higher in-sample R^2 values than individual forecasts. For out-of-sample forecasts, there are also substantial gains in including term structure and GZ predictors. Mean combination forecasts using GZ and term structure variables (Combination 2) again produce much larger out-of-sample R^2 values than individual predictors. As indicated, the out-of-sample R^2 values are all consistently positive.

Out-of-sample credit spread return predictability is of economic significance, particularly when using the GZ variables as predictors (see Panel A). Panel B of Table 9 shows that utility gains are overwhelmingly positive and much larger compared to individual forecasts. The certainty equivalent returns (utility gains) increase significantly when using the forecast combination method to predict returns. Both out-of-sample R^2 and utility gains consistently show that forecast combination generates more stable forecasts and higher utility gains for the credit spread component of returns.

5.6. Link to the Real Economy

In this section, we investigate the linkage between bond premium forecasts and real economy. A finding of a close link between these two variables will provide a rationale for economic gains of out-of-sample forecasts.

5.6.1. Corporate Bond Premium Forecasts and NBER Business-Cycle Phases

(Fama and French 1989) suggest that risk premium forecasts should be closely linked to macroeconomic performance. (Cochrane 2007) argues that asset premium forecasts are more plausibly related to macroeconomic risk if risk premium forecasts can be shown closely linked to business cycles. In light of the literature, we investigate the relation between corporate bond premium forecasts and business cycles.

Figure 2 plots the forecasts of corporate bond premiums for each rating class and the whole sample, where the vertical lines indicate the NBER-dated peaks and troughs of the US economy. There are three noticeable recessions over the out-of-sample forecast period with business-cycle troughs (peaks) occurring around 1991:1 (1990:3), 2001:4 (2001:1), and 2008:3. As shown, corporate bond premiums decline during expansions and rise during recessions. The GZ and term structure predictors produce a corporate bond premium forecast that closely tracks NBER business-cycle phases and the pattern of bond premium forecasts is consistent with the views of (Fama and French 1989; Cochrane 1999). Bond return predictability is attributed to time-varying risk premiums associated with temporal variations in economic conditions and that our return predictors track these variations.

5.6.2. Out-Of-Sample Forecasts under Different Economic Regimes

The literature on equity return predictability has shown that investor risk aversion and asset risk increase during economic downturns leading to a higher risk premium (Fama and French 1989; Cochrane 1999). (Liew and Vassalou 2000) show that returns of the Fama–French factor portfolio are associated with future economic growth. High portfolio returns precede economic expansion and low portfolio returns precede economic recession. (Rapach et al. 2010) find that out-of-sample gains in equity premium forecasts are more evident during low-growth periods.

Bonds and stocks are the claims to asset value of the same firm. If expected stock returns vary with business cycles, expected bond returns should follow suit. To further explore the economic sources of bond premium forecasts, we examine the predictability of corporate bond returns in different economic regimes. We use the recession probability data provided by the Federal Reserve Bank of St. Louis, and the real GDP growth rate to define good, normal and bad economic growth periods. We sort these variables into the top, middle and bottom terciles and report the out-of-sample R^2_{OS} for good (top) and bad (bottom) economies.

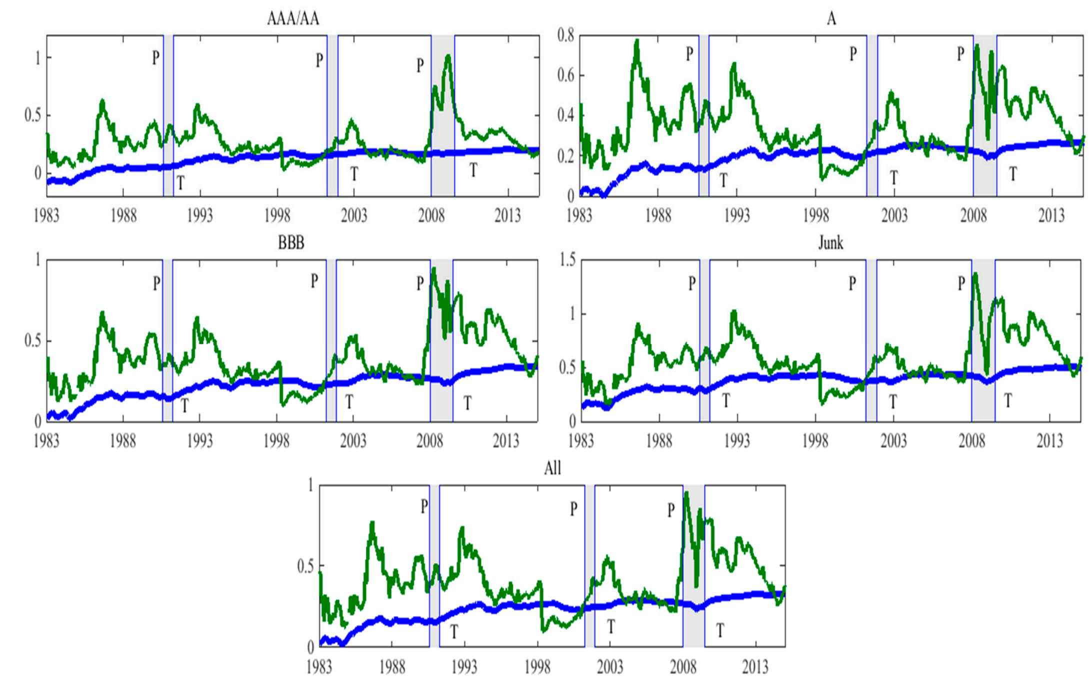

Figure 2. Corporate bond risk premium forecast of GZ-family predictors and National Bureau of Economic Research (NBER)-dated business-cycle turning points, 1983–2014. The solid and dotted line represent the mean combination forecast by GZ-family predictors and historical mean forecast, respectively. Vertical lines indicate NBER-dated business-cycle peaks (P) and troughs (T).

Table 10 reports the results of out-of-sample forecasts in good and bad economic regimes. We focus on the forecasts using multiple predictors and the combination method as they perform better than the forecasts by individual predictors. Panel A reports the results that use the recession probability of Federal Reserve Bank of St. Louis to sort different conditions of the economy. As shown, out-of-sample gains in terms of $R^2_{OS}s$ are much higher during the low-growth period. For the forecasts using multiple regressions, on average the out-of-sample R^2 statistics are about five times higher during the low-growth than during the high-growth periods. For combination forecasts, the first and second combinations continue to outperform the third combination and in all cases, returns are more predictable during economic downturns. The results show a similar pattern for short- and long-term bonds. Return predictability varies with business cycles and this pattern is more pronounced for speculative-grade bonds.

Panel B of Table 10 shows that the predictability of bond returns is also higher during the low GDP growth period. Combination forecasts again deliver greater out-of-sample utility gains than multiple predictor regressions. Overall, there is evidence that the predictability of the corporate bond premium is linked to macroeconomic conditions and returns are more predictable during the low-growth period.

5.7. GZ Spreads of Different Ratings

(Gilchrist and Zakrajsek 2012) calculate their credit spread index and excess bond premium using the bond data in all rating categories. We can construct GZ credit spreads using bonds of different ratings and compare their predictive power. If the credit spread of speculative-grade bonds is more sensitive to business cycles, the GZ index based on these bonds would contain better information to forecast returns than that based on investment-grade bonds.

Table 11 reports the results using the GZ predictors constructed from speculative- and investment-grade bonds, respectively. For brevity, we focus on the results of GZ spread (AGZ) (Panel A) and mean combination forecast of GZ family predictors (Panel B). We report the differences in the in- and out-of-sample R_{OS}^2 and utility gains for AGZ and mean combination forecasts.

The results show that GZ predictors using speculative-grade bonds have higher predictive power for returns than those using investment-grade bonds. When the AGZ variable is used to predict the annual corporate bond returns, on average the speculative-grade AGZ outperforms the investment-grade AGZ by 9.45% for in-sample R^2, by 13.03% for out-of-sample R^2, and by 0.56% for utility gains. The improvement is greater for short-term bonds than for long-term bonds. The results of mean combination forecasts are similar. The results suggest that the GZ credit spread of speculative-grade bonds contains more information for expected corporate bond returns.

5.8. Macroeconomic and Policy Uncertainty Variables

Bond spread theory suggests that yield spreads of corporate bonds are determined by firm value, interest rates, and cash flows (see Merton 1974; Collin-Dufresne et al. 2001). To the extent that bond returns can be approximated by yield spread changes (see Elton et al. 2001), variables that affect firm value and cash flows will affect corporate bond returns. The literature has shown that macroeconomic variables, such as inflation and industrial production, can predict bond returns (see Joslin et al. 2014). In this section, we investigate the predictive power of macroeconomic and policy uncertainty for corporate bond returns and whether including these variables may further improve return predictability. We download macroeconomic data from the Federal Reserve Bank of St. Louis and employ the policy uncertainty index of (Baker et al. 2016).

Table 10. Out-of-sample forecasts under different economic growth regimes. This table reports the out-of-sample R_{OS}^2 of predictive regressions under different economic growth regimes. The forecast horizon is yearly. The predictors include the default spread (DFS), the issuer quality index (IQ), the commercial paper spread (CPS), the actual GZ spread (AGZ), the predicted GZ spread without option adjustment (PGZ1), the predicted GZ spread with option adjustment (PGZ2), the excess bond premium excluding the effect of option adjustment on callable bonds (EBP), the three-month Treasury bill rate (TBL), and term spread (TMS). Reported are the results of forecasts using multiple predictors. Mean combinations 1, 2, and 3 use the mean of individual forecasts using the GZ family predictors, the GZ family predictors and the TBL and TMS, and all predictors, respectively. We divide the whole sample period into good, normal, and bad economic growth regimes using the recession probability data (Panel (**A**)) and the real GDP growth rates (Panel (**B**)). The signs ^{a}, ^{b}, and ^{c} denote the significance at 1%, 5%, and 10% levels, respectively.

		Panel (A) Annual R_{OS}^2 Based on Recession Probabilities														
		Bad (%)					**Good (%)**					**Difference (%)**				
	Predictor	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolio	TBL + TMS + EBP	−21.77	22.64 ^{a}	41.58 ^{a}	30.48 ^{a}	34.31 ^{a}	−2.57	6.22 ^{a}	12.10 ^{a}	17.52 ^{a}	8.20 ^{a}	−19.20	16.42	29.48	12.96	26.11
	Combination 1	7.01 ^{a}	22.79 ^{a}	36.04 ^{a}	32.25 ^{a}	35.81 ^{a}	4.43 ^{a}	0.68 ^{b}	11.99 ^{a}	12.88 ^{a}	8.55 ^{a}	2.58	22.11	24.05	19.37	27.26
	Combination 2	15.47 ^{a}	23.02 ^{a}	35.33 ^{a}	30.02 ^{a}	34.73 ^{a}	8.07 ^{a}	8.04 ^{a}	18.07 ^{a}	18.79 ^{a}	15.00 ^{a}	7.40	14.98	17.26	11.23	19.73
	Combination 3	5.62 ^{a}	16.20 ^{a}	33.49 ^{a}	26.71 ^{a}	28.66 ^{a}	−6.14	−6.72	−2.07	−1.90	−5.02	11.76	22.92	35.56	28.61	33.68
Short-duration portfolio	TBL + TMS + EBP	−74.31	13.16 ^{a}	44.01 ^{a}	37.20 ^{a}	44.19 ^{a}	5.47 ^{a}	3.60 ^{a}	19.91 ^{a}	8.15 ^{a}	15.78 ^{a}	−79.78	9.56	24.10	29.05	28.41
	Combination 1	−3.26	22.27 ^{a}	36.36 ^{a}	32.62 ^{a}	41.81 ^{a}	−9.52	−20.74	−2.08	−0.93	−6.16	6.26	43.01	38.43	33.55	47.96
	Combination 2	4.94 ^{a}	21.27 ^{a}	31.46 ^{a}	28.51 ^{a}	36.59 ^{a}	3.02 ^{a}	−5.30	7.78 ^{a}	3.37 ^{a}	4.71 ^{a}	1.92	26.57	23.67	25.15	31.88
	Combination 3	−2.65	21.71 ^{a}	42.28 ^{a}	36.82 ^{a}	45.29 ^{a}	−19.11	−29.45	−12.67	−10.16	−21.13	16.46	51.15	54.95	46.99	66.41
Long-duration portfolio	TBL + TMS + EBP	13.30 ^{a}	32.72 ^{a}	44.59 ^{a}	37.12 ^{a}	44.58 ^{a}	4.52 ^{a}	17.14 ^{a}	−13.81	17.32 ^{a}	7.27 ^{a}	8.78	15.58	58.40	19.80	37.31
	Combination 1	15.61 ^{a}	30.51 ^{a}	40.44 ^{a}	39.38 ^{a}	43.11 ^{a}	8.40 ^{a}	13.64 ^{a}	2.65 ^{a}	4.20 ^{a}	11.26 ^{a}	7.21	16.86	37.78	35.18	31.84
	Combination 2	23.50 ^{a}	32.24 ^{a}	42.32 ^{a}	38.19 ^{a}	44.20 ^{a}	11.12 ^{a}	19.57 ^{a}	8.32 ^{a}	16.41 ^{a}	18.12 ^{a}	12.37	12.67	34.00	21.78	26.08
	Combination 3	10.65 ^{a}	20.41 ^{a}	36.67 ^{a}	25.88 ^{a}	32.85 ^{a}	1.48 ^{a}	2.69 ^{a}	−6.65	−13.23	−2.49	9.17	17.72	43.32	39.11	35.34
		Panel (B) Annual R_{OS}^2 Based on Real GDP Growth Rates														
		Bad (%)					**Good (%)**					**Difference (%)**				
	Predictor	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolio	TBL + TMS + EBP	−18.48	18.53 ^{a}	36.38 ^{a}	28.64 ^{a}	28.87 ^{a}	−4.82	0.75 ^{a}	4.43 ^{a}	7.77 ^{a}	1.61 ^{a}	−13.66	17.78	31.95	20.88	27.26
	Combination 1	0.66 ^{a}	16.95 ^{a}	30.38 ^{a}	31.61 ^{a}	30.44 ^{a}	1.43 ^{a}	−3.12	3.21 ^{a}	7.50 ^{a}	3.20 ^{a}	−0.77	20.07	27.17	24.11	27.25
	Combination 2	7.56 ^{a}	18.81 ^{a}	30.78 ^{a}	29.66 ^{a}	30.50 ^{a}	6.13 ^{a}	5.23 ^{a}	11.30 ^{a}	12.44 ^{a}	10.62 ^{a}	1.43	13.58	19.48	17.22	19.88
	Combination 3	−3.79	10.06 ^{a}	26.48 ^{a}	24.07 ^{a}	21.83 ^{a}	−3.77	−5.92	−3.55	−2.42	−4.32	−0.02	15.98	30.04	26.49	26.15
Short-duration portfolio	TBL + TMS + EBP	−55.24	12.77 ^{a}	43.62 ^{a}	36.17 ^{a}	41.21 ^{a}	8.59 ^{a}	1.83 ^{a}	6.69 ^{a}	0.08 ^{a}	9.62 ^{a}	−63.82	10.94	36.93	36.10	31.59
	Combination 1	−9.30	14.34 ^{a}	32.55 ^{a}	30.43 ^{a}	35.61 ^{a}	−4.57	−20.04	−9.42	−3.24	−8.44	−4.73	34.37	41.97	33.67	44.05
	Combination 2	0.91 ^{a}	16.62 ^{a}	28.99 ^{a}	27.01 ^{a}	32.27 ^{a}	7.52 ^{a}	−4.12	0.42 ^{a}	−0.78	2.11 ^{a}	−6.61	20.74	28.57	27.78	30.16
	Combination 3	−10.61	12.84 ^{a}	37.40 ^{a}	33.16 ^{a}	37.10 ^{a}	−15.83	−29.32	−14.21	−8.68	−21.06	5.21	42.16	51.60	41.85	58.16
Long-duration portfolio	TBL + TMS + EBP	8.84 ^{a}	27.32 ^{a}	35.11 ^{a}	31.05 ^{a}	33.79 ^{a}	−3.27	12.68 ^{a}	−29.22	20.91 ^{a}	3.97 ^{a}	12.10	14.64	64.33	10.14	29.82
	Combination 1	5.98 ^{a}	23.30 ^{a}	28.85 ^{a}	36.94 ^{a}	33.94 ^{a}	5.72 ^{a}	11.52 ^{a}	−1.25	2.17 ^{a}	8.87 ^{a}	0.26	11.78	30.10	34.77	25.08
	Combination 2	12.24 ^{a}	25.99 ^{a}	32.32 ^{a}	35.97 ^{a}	35.93 ^{a}	8.56 ^{a}	18.56 ^{a}	5.34 ^{a}	15.12 ^{a}	17.38 ^{a}	3.68	7.43	26.98	20.85	18.54
	Combination 3	2.02 ^{a}	13.70 ^{a}	23.16 ^{a}	20.45 ^{a}	22.23 ^{a}	3.17 ^{a}	5.08 ^{a}	−3.35	−12.28	−0.91	−1.15	8.62	26.51	32.73	23.14

Table 11. Predictions of investment- and speculative-grade GZ variables. This table reports the difference of prediction results of actual GZ spread (AGZ) and mean combination of GZ variables using speculative- and investment-grade bonds to construct the GZ variables. Panel (**A**,**B**) reports the results of forecasts using AGZ and mean combination of GZ-family predictors, respectively.

		Panel (A) AGZ														
		Monthly (%)					Quarterly (%)					Yearly (%)				
	Portfolio	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Difference in in-sample R^2	Rating	1.45	2.56	3.33	5.06	3.79	2.00	3.50	4.97	9.02	5.67	3.20	7.56	7.78	13.29	9.45
	Short-term	2.13	3.58	3.95	4.53	5.17	3.17	4.87	5.24	9.45	8.21	4.48	7.60	3.47	14.40	11.29
	Long-term	1.23	1.98	1.78	4.57	3.00	1.15	3.06	2.90	8.48	4.44	1.63	6.36	4.62	13.75	7.53
Difference in out-of-sample R^2	Rating	−0.91	0.30	0.87	4.86	2.23	−4.27	2.38	4.22	12.53	6.19	−6.02	7.82	9.18	25.09	13.03
	Short-term	−5.36	0.08	3.90	3.91	4.36	−11.63	2.74	6.90	12.58	12.14	−11.86	6.78	10.92	22.19	18.44
	Long-term	−0.59	−0.21	0.75	3.22	1.91	−2.11	1.86	2.52	10.71	3.94	−3.53	5.91	1.34	27.01	8.39
Difference in utility gains	Rating	−0.27	−0.05	0.51	2.31	0.10	−0.34	0.30	0.44	3.04	0.87	−0.26	0.10	0.19	1.83	0.56
	Short-term	0.20	0.40	1.28	2.67	1.06	0.29	0.73	1.39	4.17	1.32	0.36	0.43	0.62	2.14	0.51
	Long-term	−0.03	0.55	1.14	1.33	1.16	−0.49	0.83	0.38	2.22	0.56	−0.47	0.25	0.31	1.14	0.19
		Panel (B) Mean Combination Using GZ Variables														
		Monthly (%)					Quarterly (%)					Yearly (%)				
	Portfolio	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Difference in out-of-sample R^2	Rating	2.46	3.05	3.87	4.24	4.41	10.52	16.24	21.78	14.16	18.38	−4.07	2.71	7.90	19.45	9.73
	Short-term	−2.96	0.44	3.87	3.14	4.10	−7.24	6.05	11.41	14.74	14.74	−33.00	−11.72	0.91	17.74	4.88
	Long-term	1.80	3.17	8.13	3.10	3.90	9.18	17.22	34.41	11.45	19.65	−4.43	12.38	32.00	21.70	14.07
Difference in utility gains	Rating	0.23	−0.20	0.33	2.28	0.57	0.27	0.51	0.16	2.77	1.07	0.48	0.05	0.10	1.98	0.47
	Short-term	0.45	0.24	0.66	2.81	0.58	0.52	0.38	1.03	3.55	0.70	0.39	0.16	0.41	2.55	0.20
	Long-term	−1.49	−0.10	1.47	1.68	0.28	−1.36	0.35	0.44	2.51	0.16	−0.66	0.86	0.71	1.51	0.52

Table 12 reports the results of predictive regressions using macroeconomic and policy uncertainty variables.[6] Among macroeconomic variables, industrial production (IPG) and inflation rates (CPI) have more predictive power. Interestingly, the economic uncertainty index of (Baker et al. 2016) has higher predictive power than macroeconomic variables. However, the multiple regression that include term structure variables, GZ index (EBP), and all macroeconomic variables and policy uncertainty index does not perform well. This evidence is consistent with the finding of (Welch and Goyal 2008) that multiple regressions including too many predictors generally perform poorly as noises in these variables compound. In this circumstance, the best way to combine predictors is to use the combination forecast method (see Rapach et al. 2010). We find that this is indeed the case. As shown in the table, mean combination produces much better forecasts. In addition, combining GZ, term structure, and macroeconomic/uncertainty variables (Combination 2) produces better forecasts than combining just macroeconomic and policy uncertainty variables (Combination 1).

The results show that macroeconomic and policy uncertainty variables help improve the forecast for corporate bond returns. One important issue is whether the GZ variables contain important information over and beyond these variables. To investigate this issue, we employ the test method of (Harvey et al. 1998). The null hypothesis is that model i forecast (including all macroeconomic/uncertainty variables) encompasses model j forecast (including all GZ variables), 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

$$MHLN = \frac{(T-k-1)}{(T-k)}\left[\hat{V}(\bar{d})^{-1/2}\right]\bar{d}, \tag{9}$$

where $\bar{d} = \frac{1}{T-k}\sum_{t=1}^{T-k} d_{t+k}$, $\hat{V}(\bar{d}) = (T-k)^{-1}\hat{\phi}_0, \hat{\phi}_0 = (T-k)^{-1}\sum_{t=1}^{T-k}(d_{t+k} - \bar{d})^2$ and MHLN has a t distribution with T-k-1 degree of freedom.

[6] For brevity, coefficient estimates and t values are reported in the file of Supplementary Materials online.

Table 12. Policy uncertainty, macroeconomic activity, and return predictability. This table reports in- and out-of-sample R^2_{OS} and utility gains using policy uncertainty and macroeconomic condition. The economic uncertainty index (EPU) is from (Baker et al. 2016), and macroeconomic variables include industrial production growth (IPG), nonfarm payroll (PAY), inflation (CPI), and unemployment rate (UNEM) from the Federal Reserve. MP denotes the multiple predictive regression using EPU, IPG, PAY, CPI, and UNEM jointly. Combination forecast 1 is the mean combination using EPU, IPG, PAY, CPI, and UNEM, while combination forecast 2 is mean combination using all predictors. We use the method of (Clark and West 2007) to test the significance of R^2_{OS}, and follow (Hodrick 1992) to adjust for standard errors when the forecast horizon is beyond one month. The signs [a], [b], and [c] denote the significance at 1%, 5%, and 10% levels, respectively.

		Monthly In-Sample R^2					Monthly Out-Of-Sample R^2_{OS}					Monthly Utility Gains				
	Predictor	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolio	EPU	1.36	3.33	3.27	5.45	4.24	2.45 [a]	4.56 [a]	4.43 [a]	6.78 [a]	6.05 [a]	0.41	2.68	2.71	4.23	2.01
	IPG	0.05	1.78	1.36	3.37	1.78	−1.29	2.12	1.52	4.55 [b]	2.29 [c]	−0.78	−0.48	−1.08	0.04	−1.03
	PAY	1.48	4.05	4.69	6.33	4.92	−0.55	5.27 [a]	6.76 [a]	8.36 [a]	7.06 [a]	−0.38	0.64	0.20	1.76	0.17
	CPI	1.59	1.68	2.82	2.68	2.93	0.85 [b]	2.33 [b]	3.76 [a]	3.30 [a]	4.00 [a]	1.29	2.48	3.07	2.60	2.04
	UNEM	0.58	2.76	3.73	4.60	3.56	−1.81	2.79 [a]	4.37 [a]	5.51 [a]	3.97 [a]	−2.38	0.04	−0.88	2.90	−1.44
	MP	2.08	4.24	6.52	10.31	6.69	−0.01	1.50 [a]	4.40 [a]	8.56 [a]	4.54 [a]	−1.81	0.28	0.24	3.83	−0.22
	TBL + TMS + EBP + MP	1.60	4.66	6.73	10.81	7.38	−1.94	1.46 [a]	4.57 [a]	10.39 [a]	6.51 [a]	−2.48	−0.21	1.57	3.77	0.47
	Combination 1						1.46 [b]	5.34 [b]	5.70 [b]	7.55 [a]	6.75 [a]	0.29	2.14	2.14	2.98	1.64
	Combination 2						1.75 [b]	3.85 [c]	4.41 [b]	5.61 [a]	5.10 [a]	0.65	2.36	2.41	2.64	2.11
		Quarterly In-Sample R^2					**Quarterly Out-Of-Sample R^2_{OS}**					**Quarterly Utility Gains**				
	Predictor	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolio	EPU	1.54	7.01	9.62	14.10	10.61	1.17 [a]	7.41 [a]	12.36 [a]	16.54 [a]	13.24 [a]	0.39	2.35	2.33	3.55	1.41
	IPG	0.09	3.30	3.16	5.19	3.64	−1.88	4.12 [b]	4.01 [b]	6.75 [a]	5.36 [b]	−0.59	−0.05	−0.62	0.03	−0.85
	PAY	2.99	7.46	9.53	10.47	9.23	−0.46	8.93 [a]	14.25 [a]	13.27 [a]	13.51 [a]	−0.37	1.02	0.62	1.28	0.21
	CPI	3.11	3.15	4.97	4.73	4.67	1.44 [b]	3.77 [a]	6.72 [a]	4.52 [a]	6.03 [a]	1.32	2.64	2.86	1.85	1.82
	UNEM	1.25	5.62	7.73	8.66	6.90	−3.37	6.05 [a]	9.53 [a]	10.71 [a]	8.03 [a]	−2.06	0.75	0.11	2.80	−1.20
	MP	4.89	9.49	16.05	21.28	15.59	−5.98	−3.52	8.16 [a]	14.43 [a]	5.98 [a]	−1.70	0.07	0.92	3.10	−0.68
	TBL + TMS + EBP + MP	5.77	13.02	18.69	23.69	18.82	−4.02	2.61 [a]	8.61 [a]	11.82 [a]	9.00 [a]	−3.36	0.29	0.31	1.28	−1.18
	Combination 1						2.28 [a]	9.56 [b]	13.02 [a]	14.47 [a]	13.53 [a]	0.12	2.26	2.24	2.43	1.43
	Combination 2						3.12 [a]	6.56 [b]	10.11 [a]	9.79 [a]	10.22 [a]	0.28	2.35	2.48	2.15	1.77
		Yearly In-Sample R^2					**Yearly Out-Of-Sample R^2_{OS}**					**Yearly Utility Gains**				
	Predictor	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**	**AAA/AA**	**A**	**BBB**	**Junk**	**All**
Rating portfolio	EPU	2.33	12.70	18.73	20.87	17.08	2.92 [a]	11.52 [a]	19.70 [a]	15.24 [a]	17.02 [a]	0.56	1.90	1.77	2.90	1.08
	IPG	2.82	11.68	15.01	14.30	12.61	−2.60	18.18 [a]	20.70 [a]	12.97 [a]	18.60 [a]	−0.52	−0.23	−0.75	0.47	−0.83
	PAY	10.76	19.00	27.15	23.90	23.18	1.63 [a]	25.51 [a]	39.06 [a]	27.70 [a]	34.31 [a]	−0.11	0.95	0.79	1.31	0.35
	CPI	4.02	2.89	5.34	4.63	4.72	1.55 [a]	0.37 [c]	4.56 [a]	0.27 [c]	2.34 [a]	0.62	1.01	1.14	0.83	0.95
	UNEM	3.53	11.36	15.76	13.66	12.86	−11.43	11.92 [a]	17.23 [a]	14.78 [a]	13.93 [a]	−1.99	0.34	0.18	2.29	−0.89
	MP	12.33	26.07	39.49	47.60	37.60	−25.75	−1.43	20.22 [a]	24.35 [a]	13.93 [a]	−1.18	−0.34	0.12	2.35	−0.69
	TBL + TMS + EBP + MP	17.25	33.02	45.50	52.65	43.13	−22.97	−12.34	−3.47	2.63 [a]	−9.89	−3.58	−2.12	−1.94	−0.66	−4.19
	Combination 1						6.89 [a]	21.28 [a]	28.03 [a]	20.17 [a]	25.40 [a]	−0.06	1.45	1.53	1.96	0.88
	Combination 2						9.57 [a]	19.37 [a]	27.61 [a]	22.43 [a]	26.19 [a]	0.17	1.41	1.68	2.04	1.06

The MHLN tests reject the null hypothesis that the forecast using macroeconomic/policy uncertainty variables encompasses the forecast using the GZ variables. In other words, the GZ variables contain the information that macroeconomic variables do not have. The *p*-values of MHLN tests for monthly and quarterly forecasts are 0.01 and 0.02 for the full sample that includes all rated bonds. Similar results are found for bonds in different rating categories. The results suggest that the GZ variables contain important information for future corporate bond returns over and beyond that of macroeconomic and policy uncertainty variables.

6. Conclusions

In this paper, we examine the predictive power of the GZ credit spread indexes relative to conventional default spread and term structure variables. We find that the GZ credit spread variables have much more predictive power than traditional credit spread measures. The GZ variables outperform conventional credit spread and term structure variables in terms of R^2 values and economic significance. The results show that the GZ variables contain richer information for future asset returns than the usual predictors of corporate bonds.

Corporate bond premium forecasts by the GZ credit spread and term structure variables are closely linked to business cycles. The superiority of the GZ predictor is mainly due to its ability to forecast future economic activity. There is evidence that the credit spread component of bonds is predictable, not just the entire excess return. The results show that the GZ credit spread variables capture time-varying bond risk premiums. The GZ credit spread constructed from speculative-grade bond data has higher forecasting power than that formed by investment-grade bond data. Moreover, the predictive power of the GZ variables is robust to controlling for the effects of macroeconomic and policy uncertainty variables.

Our analysis provides useful information for both financial researchers and practitioners. First, our findings have important implications for theoretical modelling and asset pricing research. The evidence uncovered in this paper suggests that the term structure model of defaultable bonds should account for the phenomenon of return predictability. Using the expected return generated from the predictive model, one can assess whether the bond investors receive sufficient compensation for the risk they bear, and determine whether corporate bonds are priced properly. Second, our results provide valuable information for investors to time the corporate bond market and to enhance their portfolio performance. From the perspectives of risk management and financing, studying bond risk premiums is essential for understanding firms' interest rate exposures, as well as corporate financing choices. An efficient return forecast model provides a benchmark for evaluating investment manager performance and essential information for investors to perform optimal asset allocations. Our findings thus not only advance academic research on asset pricing but also enhance practical investment and portfolio management.

Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Table S1: Policy uncertainty, macroeconomic condition and bond return predictability, Table S2: Predictability for AAA bonds.

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Appendix A. Construction of GZ Spreads

This appendix describes the estimation procedure and the data used for constructing GZ credit spread variables, which include actual spreads (AGZ), predicted spreads without option adjustment (PGZ1), predicted spreads with option adjustment (PGZ2), and excess bond premium (EBP).

Consider a corporate bond q issued by firm i at time t. The valuation of this bond is given by

$$P_{it}[q] = \sum_{s=1}^{T} C(s)D(t_s), \tag{A1}$$

where $C(s)$ is the promised cash flow payment at time s, and $D(t) = e^{-y_{it}t}$ is the discount function at t. To calculate the price of an equivalent risk-free security with identical cash flow and maturity, $P_{it}^{f}[q]$, we discount the cash flow using continuously compounded zero-coupon Treasury rates obtained from the Treasury yield curve estimated by (Gurkaynak et al. 2007). The resulting price $P_{it}^{f}[q]$ is then used to calculate the equivalent yield of the bond with no default risk, denoted by $y_{it}^{f}[q]$. The individual credit spread is calculated as

$$S_{it}[q] = y_{it}[q] - y_{it}^{f}[q], \tag{A2}$$

where $y_{it}[q]$ is the promised yield of corporate bond q embedded in $D(t)$. This calculation of credit spreads is free of the bias that would occur when the spreads are computed by matching the corporate bond yield with the yield of a Treasury security (often through interpolation) of the same maturity.

The GZ credit spread is calculated as

$$AGZ_t = \frac{1}{N_t} \sum_i \sum_q S_{it}[q], \tag{A3}$$

with N_t equal to the number of bond/firm observations in month t, which by construction, is an arithmetic average of the credit spreads of outstanding bonds in that month.

(Gilchrist and Zakrajsek 2012) further decompose the credit spread AGZ_t into the expected and unexpected components. This requires first relating the log of credit spread on bond q of firm i at time t to a firm-specific measure of expected default DFT_{it} based on (Merton 1974) distance to default, and a vector of bond-specific characteristics ($\boldsymbol{Z_{it}}[q]$):

$$lnS_{it}[q] = \beta DFT_{it} + \gamma' \boldsymbol{Z_{it}}[q] + \varepsilon_{it}[q], \tag{A4}$$

where $\varepsilon_{it}[q]$ represents a pricing error with mean zero and standard deviation $\hat{\sigma}[q]$. This relation is estimated by least squares regression where standard errors are double clustered in firm and time and therefore are robust to both cross-sectional dependence and serial correlation.

Assuming normally distributed errors, the predicted level of the spread for bond q of firm i at time t is given by

$$\hat{S}_{it}[q] = exp\left[\hat{\beta} DFT_{it} + \hat{\gamma}' \boldsymbol{Z_{it}}[q] + \frac{1}{2}\, \hat{\sigma}_2[q]\right], \tag{A5}$$

where $\left[\hat{\beta}\ \hat{\gamma}\ \right]'$ denotes the OLS estimates of the corresponding parameters. By averaging cross bonds at time t, we can obtain the predicted component of GZ spread (PGZ) as

$$PGZ_t = \frac{1}{N_t} \sum_i \sum_q \hat{S}_{it}[q]. \tag{A6}$$

In (A5), DFT_{it} is measured by the distance to default calculated under the (Merton 1974) framework. The variables $\boldsymbol{Z_{it}}[q]$ include duration, amount outstanding, coupon rate, age of the bond, and an indicator if the bond has a call provision. To control for any systematic (time-invariant) differences in expected recovery rates across industries, we also include three-digit NAICS in the regression to control the industry fixed effect. The regression also includes the S&P credit rating fixed effect to capture the "soft information" for the firm's financial health, which is complementary to the option-theoretic measure of default risk. We denote the GZ spread predicted by the above variables as PGZ1. The excess bond premium in month t is then defined as

$$EBP_t = AGZ_t - PGZ1_t. \tag{A7}$$

Our data sample for calculating GZ spread includes a large number of callable bonds. To control for the effects of the call option, Treasury term structure and interest rate volatility on the spreads of callable bonds, besides the above variables, we also include the call provision, the level, slope and curvature of the Treasury yield curve, and the realized monthly volatility of the daily ten-year Treasury yield in $\boldsymbol{Z_{it}}[q]$. We denote the GZ spread predicted by incorporating these additional variables as PGZ2. We estimate the GZ variables using the data sample described in Section 4.

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