Benchmarking Individual Corporate Bonds *

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First Draft: December, 2020

This Draft: June 24, 2022

Abstract

We propose a new econometric model, *benchmark combination model (BCM)*, to estimate and decompose asset risk premia in empirical asset pricing. BCM pricing kernel is a weighted combination of the basis portfolios sorted on many asset characteristics. With a no-arbitrage objective, our approach minimizes cross-sectional pricing errors and identifies the sources of risk premia. With a 45-year sample of U.S. corporate bonds, we find that BCM outperforms prevailing factor models in pricing corporate bonds. Second, we find credit ratings, maturity, short-term reversal, momentum, and variance are primary sources of bond risk premia. Finally, incorporating machine learning forecasts into BCM shows strong evidence of return predictability.

Key Words: Characteristic-based benchmark, high-dimensional sort, corporate bond risk premia, forecast combination, machine learning, return predictability.

*We are grateful to Turan G. Bali for sharing bond factors data and Amit Goyal for sharing macroeconomic predictors data. We also thank Jianqing Fan, Zhonghao Fu, Li Guo, Jingyu He, Guangwu Liu, Xiaohu Wang, Dacheng Xiu, and Tengfei Zhang, and seminar and conference participants at City University of Hong Kong, Fudan University, University of Gothenburg, 2021 Financial Market and Corporate Governance Conference, 2021 China Accounting and Finance Conference, 37th International Conference of the French Finance Association, 2021 China International Risk Forum, 2021 SoFiE Summer School at NYU Shanghai, and 2021 China Finance Annual Meeting for constructive discussions and feedback. He (E-mail:xin.he@my.cityu.edu.hk), Feng (E-mail:gavin.feng@cityu.edu.hk), and Wang (E-mail:jwang2@cityu.edu.hk) are at College of Business, City University of Hong Kong; Wu (E-mail:chunchiw@buffalo.edu) is at School of Management, State University of New York at Buffalo.

1 Introduction

The linear factor model is a general framework in empirical asset pricing. Many characteristic-based factors are proposed for the corporate bond market. However, we find the prevailing factor models poorly explain and predict individual corporate bond returns. An alternative framework is the characteristic-based benchmark (Daniel et al., 1997; Cattaneo et al., 2020), which academic researchers relatively overlook. The sorted portfolio returns based on critical characteristics can explain the cross-sectional variation of asset returns. This nonparametric way of analyzing asset returns is a big success in the industry. Morningstar and other practitioners have been promoting the size-value equity style box and the rating-maturity fixed-income style box as benchmarks for stocks, bonds, and mutual funds.

The issuance values for the corporate bond market have become larger than for the equity market[1]. Still, the literature for methodologies and empirical evidence on pricing corporate bonds is relatively shorter than equities. Researchers usually classify individual corporate bonds into different credit rating categories (AAA/AA/A/BBB/Junk) to form portfolios. These are called basis portfolios, in which individual assets are sorted on one characteristic (ratings). Assets in the same basis portfolio are observed to bear similar credit risk. Therefore, the corresponding rating-based portfolio serves as a performance benchmark for all individual corporate bonds with the same rating. In addition to credit rating, researchers also consider maturity, momentum, reversal, liquidity, and many bond characteristics to form basis portfolios.

A rational economic benchmark should include all relevant information in these characteristics to reflect different risk exposures. However, there is a problem in high-dimensional sorts on multiple characteristics, as highlighted in Cochrane (2011). The average number of corporate bonds in each sorted portfolio decreases as the number of characteristics increases. Moreover, due to the interactions among characteristics, a sorted portfolio can contain only a few or even zero bonds. The consequences include increased estimation errors and a high chance of incorrect model identification.

[1] According to SIFMA capital markets statistics, for the U.S. corporate bond market in 2020, the outstanding value is $ 9.8 trillion and the insurance value is $ 2.3 trillion, while values for the U.S. equity market are $ 50.8 trillion and $ 390.0 billion, respectively.

We propose an alternative asset pricing framework, dubbed the benchmark combination model (BCM afterward), to alleviate the high-dimensional sort problem. Instead of sorting assets over multiple characteristics, we sort assets on each characteristic to construct basis portfolios. Then, we apply the linear combination approach on these basis portfolios associated with different characteristics to build BCM evaluation. This method preserves rich information in all relevant characteristics with a transparent, objective, and data-driven framework. The linear modeling of high-dimensional characteristics allows us to decompose returns and infer the sources of risk premia. Beyond corporate bonds, BCM offers an asset pricing research paradigm that applies to other asset classes, such as equities, commodities, and currencies.

In a nutshell, the goal of our paper is four-fold: (1) we evaluate the asset pricing performance of BCM and find our method better than prevailing factor models; (2) we tackle the high-dimensional sort difficulty for cross-sectional returns; (3) our model is intuitively interpretable and identifies the economic sources of corporate bond risk premia; and (4) we demonstrate the superiority of our model for predicting corporate bond returns.

In essence, BCM is equivalent to a non-parametric cross-sectional regression, where bond return observations are regressed on dummy variables of basis portfolios (Cattaneo et al., 2020). In addition, Kelly et al. (2019) suggest that sorting on different characteristics provides ensemble samples to dissect the cross-sectional return distribution. The same bond being evaluated by different basis portfolios for different risk exposures can be viewed as the ensemble scheme. Each basis portfolio serves as a "rational" benchmark, and their linear combination helps reduce the bias and variance for expected returns. Most importantly, a dynamic combination of basis portfolios is a tradable portfolio that keeps tracking the individual corporate bond return. The tracking error is interpreted as the pricing error. BCM minimizes the pricing errors to estimate the combination weights. Finally, the common combination weights can be used to evaluate and decompose corporate bond risk premia.

Linear factor models are commonly used in empirical asset pricing because of their excellent statistical properties and intuitive economic interpretation. However, one drawback of the factor model is that its regression estimation accuracy relies on the sample size. For this reason, most empirical studies estimate factor models for portfolios instead of individual assets. Although researchers recognize the factor model framework, constructing characteristic-sorted long-short portfolios as factors is discretionary and questionable. BCM and factor model share the exact economic purpose, benchmarking asset returns with a few tradable portfolios and decomposing risk premia. With less parametric modeling and hence less restrictive parametric assumptions, BCM stands an excellent chance to outperform conventional linear factor models in pricing individual asset returns.

We demonstrate the application of BCM using a comprehensive data set comprising 753,274 bond-month observations of 22,747 bonds by 3,620 firms from 1976 to 2020. We find that credit ratings, maturity, short-term reversal, momentum, and variance are important sources of risk premia. In particular, short-term reversal is an under-appreciated characteristic that shows high power. BCM has smaller pricing errors than conventional factor models in pricing individual corporate bond returns, and the performance is persistently good over time. In addition, there is strong evidence that the bond basis portfolio returns are predictable. The combination of portfolio-level predictions also helps predict individual bond returns. BCM combined with various machine learning models carries high out-of-sample predictive power for individual bond returns. The long-short strategy of BCM plus Random Forest delivers a monthly return of 66 bp, which cannot be explained by the five-factor model of Fama and French (1993) with a monthly alpha of 61 bp, and an annualized Sharpe ratio of 2.05 over the recent 25 years. The strategy delivers a high Sharpe ratio of 2.93 in economic expansion and makes a relatively sizeable monthly alpha of 83 bp over the dot-com bubble and the 2008 financial crisis.

Literature. Our work is related to the literature on pricing individual corporate bonds based on the framework of risk factors and characteristics. Fama and French (1993) propose a five-factor model with three equity factors and two bond market factors to explain the joint cross section of equity and bond returns. Many papers investigate various factors or anomalies for the cross section of corporate bond returns; see liquidity from Lin et al. (2011), momentum from Jostova et al. (2013), volatility from Chung et al. (2019), downside risk from Bai et al. (2019), long-term reversal from Bali et al. (2021), downside variance from Huang et al. (2021), and jump risk in Chen et al. (2022). Bredendiek et al. (2019) adopt the characteristic-driven optimal portfolio for corporate bonds, and recently, Kelly et al. (2021) create latent corporate bond factor models via Instrumental PCA and

Feng et al. (2021) create another one via deep learning. This paper studies a similar problem and provides an alternative interpretation of linear model combinations.

This paper contributes to the literature on characteristic-based benchmarks and basis portfolios. Daniel et al. (1997) provide a benchmark evaluation framework for individual equity returns and mutual fund performance, which dependently sorts on size, value, and momentum. We provide a solution to the high-dimensional sort difficulty highlighted in Cochrane (2011). Cattaneo et al. (2020) develop a theoretical work for portfolio sorting by casting it as a nonparametric estimator and presenting valid asymptotic inference. Feng et al. (2020) develop a deep learning framework to approximate the characteristic-sorted factor model, while Bryzgalova et al. (2020) and Cong et al. (2021) construct characteristic-sorted basis equity portfolios through regression trees.

Our paper is related to the literature of corporate bond return prediction. For positive predictability evidence via new methods, Hong et al. (2012) introduce nonlinear time series models, Lin et al. (2014) adopt combination forecasts, and Lin et al. (2018) develop an iterated combination approach. Chordia et al. (2017) find equity information, such as firm profitability and asset growth, can predict corporate bond returns. Bali et al. (2020) and He et al. (2021) use corporate bond and/or equity characteristics to predict corporate bond returns via machine learning, and Guo et al. (2020) also find useful yield predictors through dimension reduction.

The remainder of the paper is organized as follows. Section 2 demonstrates the characteristic-sorting mechanism, BCM pricing kernel, return prediction, comparison with factor model, and implementation details. Section 3 provides data, asset pricing performance, and return prediction results. Section 4 summarizes our main findings and concludes the paper.

2 Methodology

2.1 Motivating Benchmark Pricing

The Capital Asset Pricing Model (CAPM) claims the market factor is the single factor that should be priced in the cross section of asset return under mild assumptions (Sharpe, 1964; Lintner, 1965; Jensen et al., 1972). Besides the market factor, Merton (1973) propose Intertemporal CAPM (ICAPM), which includes an additional state variable of the economy. In ICAPM, the investors aim to maximize the expected utility of lifetime consumption while facing the risk and uncertainty in future investment opportunities. However, the choice of the state variable is never an easy decision. Since then, there is an explosion of publications on asset pricing factors that claim to proxy the true state variable. One of the pioneer works is Fama and French (1993), which propose a five-factor model for stock and bond returns.

The linear factor model framework is well-recognized by economists, statisticians, and the industry. However, the way of constructing factors is questionable. Many factors discovered in empirical finance literature are characteristic-based factors. The common practice is sorting the assets into quintile (decile) portfolios by the characteristic's value. A long-short spread portfolio is called a factor. This long-short portfolio assumes a monotonic relationship between characteristics and asset expected returns. If the relationship is U-shape, the long-short portfolio earns near-zero returns. In that case, researchers are unlikely to write a paper about it. The long-short portfolio ignores the information of the sorted portfolios in the middle.

In contrast, because of nonparametric modeling, the characteristic-based benchmark can capture nonlinear relations, e.g., U-shape and quadratic, between characteristics and expected returns. We provide simulation studies to show the efficacy of characteristic-based benchmark over the long-short factor model in Appendix A. We find the long-short factor only works when there is a factor structure and the relation between characteristics and expected returns is linear. Characteristic-based benchmark is more robust under different data generating processes than factor models.

Besides, the factor model requires parametric estimation of the factor exposure. One way is to run the time-series regression of asset returns on the factors (Fama and MacBeth, 1973). The other way is to estimate a conditional beta, assuming that there is a correlation between factor exposure and asset characteristics (Rosenberg, 1974; Avramov and Chordia, 2006). Estimating factor exposure is problematic, when we do not observe the transaction prices but the quotes, the return history is short, signal to noise ratio is small, and the factor model is not correctly specified. Luckily, benchmarking asset returns with the basis portfolio is nonparametric (Cattaneo et al., 2020), which avoids the burdening parametric estimation of factor exposure.

2.2 Characteristic-Sorted Basis Portfolios on One Dimension

We now describe the procedure to implement our model. The method starts with the formation of basis portfolios sorted on a single characteristic. The relationship between the excess return r and a single characteristic z can be formulated by the following equation, [2]

$$r_{i,t} = f(z_{i,t}) + \epsilon_{i,t}, \tag{1}$$

for $i = 1, \cdots, n_t$ and $t = 1, \cdots, T$. $f(z_{i,t})$ is the part of returns that can be explained by the characteristic-based benchmarks.

We sort individual corporate bonds on a single characteristic z and calculate the order statistics. We can partition the cross section into S number of buckets. The first bucket contains the corporate bonds with small z values, and the S-th bucket includes those with large z values. The partition P is denoted as

$$P_{s,t} = \left[z_{(\lfloor \frac{s-1}{S} n_t \rfloor),t}, z_{(\lfloor \frac{s}{S} n_t \rfloor),t} \right), \tag{2}$$

for $s = 1, \cdots, S-1$, and

$$P_{S,t} = \left[z_{(\lfloor \frac{S-1}{S} n_t \rfloor),t}, z_{(n_t),t} \right], \tag{3}$$

where $z_{(l),t}$ is the order statistic, and $\lfloor \cdot \rfloor$ is the floor operator. The characteristic $z_{i,t}$ maps to one partition. We can write the partition index as a function of characteristic $s(i) = s(z_{i,t})$. The partition index s implies the basis portfolio return $R_{s,t}$,[3]

$$f(z_{i,t}) = R_{s,t} = \frac{1}{|P_{s,t}|} \sum_{i': z_{i',t} \in P_{s,t}} r_{i',t}, \tag{4}$$

where $|P_{s,t}|$ denotes the number of bond observations in partition $P_{s,t}$.

This subsection incorporates maths formulas to define the univariate-sorted portfolio returns, one of the most popular tools in empirical finance (Cattaneo et al., 2020). The individual assets can be clustered to construct well-diversified basis portfolios based on the order statistics of a charac-

[2] $z_{i,t}$ is observed at the beginning of period t, and $r_{i,t}$ is observed at the end of period t.

[3] For demonstration, we use equal-weighted portfolio returns. It is easy to extend to value-weighted portfolio return. In empirical study, we use equal-weighted basis portfolio as the main results, and the value-weighted basis portfolio as robustness check.

teristic. The number of assets in each basis portfolio is about n_t/S. Given that n_t is large and S is small, these basis portfolios are well-diversified with many underlying assets. Thus, the basis portfolio returns are potential candidates to serve as benchmarks to price the individual assets.

2.3 High-dimensional Sort Difficulty

Implementing a high-dimensional sort is difficult as indicated by Cochrane (2011). Though the benchmark evaluation through multivariate-sort mechanism is straightforward, it can be quite challenging when there are more than three characteristics.

There are two cases of multivariate-sort on multiple characteristics, the dependent sort and the independent sort. In the case of the dependent sort, suppose the number of partitions is S for each characteristic and K is the number of characteristics. There are S^K number of partitions, and the average number of corporate bonds in each partition is $n_t/(S^K)$. For a sample of 2,000 bonds, with five partitions, and four characteristics, the average portfolio size is 3.2. Researchers hope to form portfolios containing a sufficient number of corporate bonds to represent the common risks and diversify the idiosyncratic risks. However, high-dimensional sorting shrinks the size of each portfolio dramatically. In the case of independent sort, the average portfolio size is also 3.2. But, it is very likely that some partitions contain even fewer corporate bonds, especially when characteristics are highly correlated. For more details, we provide an example of the independent sort to demonstrate the difficulty in Appendix B.

2.4 The Benchmark Combination Model

BCM is a combination approach with distinct advantages when facing a large number of characteristics in portfolio sorting. With K number of characteristics in matrix form Z and S number of partitions on each dimension, there are $K \times S$ number of univariate-sorted basis portfolios $R_{k,s,t}$. A bond i has K basis portfolios that can be the potential benchmarks, and we denote them in: [4]

$$X_{i,t} = [X_{i,t,1}, X_{i,t,2}, \cdots, X_{i,t,K}]^\intercal. \tag{5}$$

[4]For different month t, $X_{i,t,k}$ of the same i and k is possible to correspond to different s. For example, a bond i can be AAA in terms of rating now, and possibly downgraded to Junk next month.

We combine K basis portfolios into one benchmark with the common combination weight:

$$\Omega = [\omega_1, \omega_2, \cdots, \omega_K]^\intercal, \tag{6}$$

and the benchmark is:

$$f(Z_{i,t}) = \Omega^\intercal X_{i,t} = \sum_{k=1}^{K} \omega_k X_{i,t,k}. \tag{7}$$

BCM Estimation and Asset Pricing. The primary goal of BCM is to price individual corporate bonds. The estimation procedure of BCM weights follows the arbitrage pricing theory. Similar to Lin et al. (2018) and Feng et al. (2020), we formulate the estimation as an optimization problem to minimize the pricing error. To reserve the economic interpretability, we add non-negativity and sum-to-unity constraints on common combination weights. Essentially, our estimation is implemented as a constrained panel regression:

$$r_{i,t} = \Omega^\intercal X_{i,t} + \epsilon_{i,t}, \tag{8}$$

$$\text{with} \sum_{k=1}^{K} \omega_k = 1, \omega_k \geq 0.$$

The panel regression helps to identify important sources of risk when decomposing the risk premia for individual corporate bond returns. The important benchmarks will have positive weights, and the trivial benchmarks will be pushed to zero with the two constraints. We provide a bootstrap test for the combination weights in Section 2.6.

In machine learning terminology, BCM is an ensemble method, which takes advantage of many weak models and gets a strong model. In terms of economic interpretation, the $\Omega^\intercal X_{i,t}$ is a replicating (synthetic) portfolio for individual bond i at time t with a minimal pricing error. The two constraints are economically tacit. The sum-to-unity constraint is a budget constraint when we do replicating and rebalancing. The non-negativity constraint is a no-short-selling constraint, as we know it is much more expensive to short corporate bonds than stocks. If we remove the two constraints, we do find negative numbers, and the total budget deviates slightly from one in the unreported empirical findings.

For robustness, we provide two other specifications: LASSO, and step-wise selection. Their empirical results are close to the constrained panel regression in Eq. 8. Please find more details in Section 3.2.

BCM Return Prediction. In BCM framework, the conditional forecast for individual bond returns is straightforward:

$$E_t(r_{i,t+1}) = \sum_{k=1}^{K} \omega_{k|t} E_t(X_{i,t+1,k}), \tag{9}$$

where $E_t(r_{i,t+1})$ is the conditional expectation of asset i's return at time $t+1$ based on information up to time t, $w_{k|t}$ is the combination weight estimated at time t, and $E_t(X_{i,t+1,k})$ is the conditional expectation of basis portfolio returns.

To understand $E_t(X_{i,t+1,k})$, it is a prediction for the basis portfolio return. The corporate bond portfolio returns are predictable, according to Hong et al. (2012); Lin et al. (2014, 2018). Given asset i, time t, and characteristics k, we can find the sorting index s. Actually, $X_{i,t+1,k}$ is a basis portfolio return, and we can denote it as $R_{k,s,t+1}$. We formulate the prediction problem in a general predictive function $g(\cdot)$:

$$E_t(X_{i,t+1,k}) = E_t(R_{k,s,t+1}) = g_{k,s}(\widetilde{Z}_{k,s,t}, x_t), \tag{10}$$

where two groups of predictors are included: $\widetilde{Z}_{k,s,t}$ are aggregated characteristics for different basis portfolios s of characteristic k, and x_t are macroeconomic predictors up to time t. We are agnostic to function $g(\cdot)$, and try to use predictive (machine learning) models to approximate it. The details of predictive modeling is in Section 2.6. We plug the forecast $E_t(X_{i,t+1,k})$ into Eq. 9 to predict individual corporate bond returns.

2.5 Connection with Factor Model

BCM provides a linear pricing kernel for individual corporate bond returns. A replicating (synthetic) portfolio is implied for the individual corporate bonds, which allocates a capital budget on basis portfolios. The conventional factor models have a similar pricing kernel interpretation. For example, the pricing kernel of CAPM for asset i is the product of two components: the factor loading β_i and the market factor f_t, and the formulation is

$$\beta_i \times f_t. \tag{11}$$

The CAPM provides a replicating portfolio of individual asset returns, which allocates β_i weight to the market factor. The replicating portfolio captures the systematic risk of an individual asset, and provides an economically interpretable benchmark for individual asset evaluation.

The estimation and interpretation for BCM are similar to the multi-factor model under the no-arbitrage condition in linear modeling. However, the multi-factor model estimates factor loadings for different assets ($N \times K$ parameters for a K-factor model to N assets). By contrast, our BCM uses all assets to estimate the common combination weights (K parameters for K characteristics). BCM has a large estimation sample with a small number of parameters.

2.6 Implementation Details

Implementing our method involves two steps. First, we estimate the common combination weights. We perform the constrained panel regression in Eq. 8 for all the observations. That is the in-sample estimation of combination weights. For out-of-sample estimation, we update the model annually using the rolling window of the past 60 months. To obtain the statistical significance of combination weights, we employ 1,000 bootstrap samples and report the non-negative estimation frequency for each benchmark to measure the significance of weights. A variable that appears more than 90% of bootstraps is deemed significant, while less than 10% means the variable is not significant.

Second, we build the return forecasts for the basis portfolios sorted on each one of the characteristics. Specifically, we train the predictive model by time-series modeling. Besides macroeconomic predictors, the predictive model for AAA portfolio only uses its characteristics and does not involve data from any other basis portfolio. We specify the training data as the rolling window of the past 20 years, update the model annually, and predict the 12 monthly observations in the following year. The predictive modeling design follows He et al. (2021). We consider five major forecasting methods, including historical average, mean combination, principal component regression, LASSO, and Random Forest. The predictive models are briefly introduced in Appendix C.

2.7 Performance Measures

Pricing Measure. Once the weights are estimated, we use Eq. 7 to construct our model-implied return benchmark for each individual corporate bond. Given the targets are individual asset returns, we adopt the pricing performance measures total R^2 and predictive R^2 introduced in Kelly et al. (2019). Both measures can be used for in-sample and out-of-sample studies.

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t} - \sum_{k=1}^{K}\hat{\omega}_k X_{i,t,k}\right)^2}{\sum_{i,t} r_{i,t}^2}, \tag{12}$$

where $\hat{\omega}_k$ is the estimate of weight. The total R^2 represents the fraction of the return variation explained by the contemporaneous realization of basis portfolio returns, aggregated over all assets and all periods. For in-sample pricing exercises, $\hat{\omega}_k$ is estimated with the whole sample of interest. For out-of-sample pricing exercises, the weights are estimated in a rolling-window manner with the available information up to time $t-1$, denoted as $\hat{\omega}_k = \hat{\omega}_{k|t-1}$.

We calculate the predictive R^2 as follows:

$$\text{Predictive } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t} - \sum_{k=1}^{K}\hat{\omega}_k \bar{X}_{i,t-1,k}\right)^2}{\sum_{i,t} r_{i,t}^2}, \tag{13}$$

where $\bar{X}_{i,t-1,k}$ denotes the sample average of the basis portfolio returns. For in-sample analysis, $\bar{X}_{i,t-1,k}$ is the sample mean of basis portfolio return. For out-of-sample analysis, $\bar{X}_{i,t-1,k}$ is the historical average by time $t-1$. As a reminder, the basis portfolio index follows the one at time t. For example, a bond is currently AAA in terms of rating, we use the AAA portfolio moving average as $\bar{X}_{i,t-1,k}$, although it may belong to Junk two months ago. The predictive R^2 represents the fraction of the realized return variation explained by the model-implied expected returns. We use similar performance measures for factor model.

Prediction Measure. We calculate the prediction error for basis portfolio return $\hat{R}_{k,s,t}$, and compare with the 20-year moving average $\bar{R}_{k,s,t}$. The conventional form of out-of-sample R^2 is:

$$R^2_{OOS,k,s} = 1 - \frac{\sum_t (R_{k,s,t} - \hat{R}_{k,s,t})^2}{\sum_t (R_{k,s,t} - \bar{R}_{k,s,t})^2}, \text{ for } k \text{ in } 1, \cdots, K, \text{ and } s \text{ in } 1, \cdots, S. \tag{14}$$

For brevity, we aggregate the prediction errors across the five portfolios sorted one characteristic k.

$$R^2_{OOS,k} = 1 - \frac{\sum_{s=1}^{S=5} \sum_t (R_{k,s,t} - \hat{R}_{k,s,t})^2}{\sum_{s=1}^{S=5} \sum_t (R_{k,s,t} - \bar{R}_{k,s,t})^2}, \text{ for } k \text{ in } 1, \cdots, K. \tag{15}$$

We evaluate the predictability of individual bond returns with the out-of-sample R^2 below:

$$R^2_{OOS} = 1 - \frac{\sum_{i,t} (r_{i,t} - E_t(r_{i,t+1}))^2}{\sum_{i,t} (r_{i,t} - \bar{r}_{i,t})^2}. \tag{16}$$

where the baseline prediction $\bar{r}_{i,t}$ is the 20-year moving average return for the corresponding rating basis portfolio.[5] The $\bar{r}_{i,t}$ is a stronger prediction than zero for fixed-income securities.

2.8 Fama-MacBeth Tests

The above metrics are aggregate measures over all time periods. However, the drawbacks for such aggregate measures are that they cannot reflect the performance variation over time and can be dominated by extremely volatile periods. To overcome this problem, we follow He et al. (2021) and adopt the Fama and MacBeth (1973)-style time-series average measures for R^2. In particular, we aggregate the information in the large cross section for each time period to obtain the R^2_t. For example, we can calculate the periodical version of total R^2_t as

$$\text{Total } R^2_t = 1 - \frac{\sum_i \left(r_{i,t} - \sum_{k=1}^{K} \hat{\omega}_k X_{i,t,k} \right)^2}{\sum_i r^2_{i,t}}. \tag{17}$$

Therefore, we are able to perform the Fama-MacBeth test on the average performance for the

[5]For example, a rating AAA bond uses the average returns of the rating AAA portfolio as the $\bar{r}_{i,t}$ in denominator.

time series $\{R_t^2\}_{t=1}^T$ with the following hypothesis with Newey and West (1987) standard errors,

$$\text{H0: } \overline{R^2} > 0\,;\ \text{H1: } \overline{R^2} \leq 0.$$

3 Empirical Results

3.1 Data

Returns The corporate bond data is from four sources: the Lehman Brother Fixed Income (LBFI) database, DataStream, the National Association of Insurance Commissioners (NAIC) database, and the Enchanced Trade Reporting and Compliance Engine (TRACE) database. We combine the data from these sources to get a large sample. When there are duplicate observations from multiple sources, we keep only one of them by a priority rank. The high to low priority rank is TRACE, NAIC, LBFI, and DataStream. Whenever there is a choice, we prefer the transaction-based return data (TRACE) to the return data based on quotes and matrix calculations (LBFI). The enhanced TRACE data starts in 2002. Using the LBFI and NAIC data extends our sample to early 1973.

We calculate corporate bond returns using the combined sample. The monthly corporate bond return at time t is calculated as follows:

$$R_t = \frac{(P_t + A_t) + C_t - (P_{t-1} + A_{t-1})}{P_{t-1} + A_{t-1}}, \tag{18}$$

where P_t is the price, A_t is the accrued interest, and C_t is the coupon payment. We obtain excess return by subtracting the three-month Treasury bill rate from the raw return. Our sample excludes bonds with embedded options and bonds with maturity less than one year or longer than thirty years. Summary statistics of the bond sample are shown in Table 1.

[Insert Table 1 here]

Characteristics We collect 20 corporate bond characteristics covering three categories: fundamental characteristics (e.g., ratings, maturity), return-distribution characteristics (e.g., momentum, reversal), and covariance with common risk factors (e.g., beta of term factor and default factor). A list of characteristics is at Table D.1. The sample period runs from January 1973 through September 2020. Because we need three years of data to calculate the return-based characteristics, the full sample of predictors starts from January 1976.

Based on each characteristic, we construct the basis portfolios (univariate-sorted quintile portfolios) and rebalance them every month. We calculate the basis portfolio returns as the equally-weighted average of the underlying assets' returns. Following Feng and He (2022), the aggregated characteristics of the basis portfolios are the equally-weighted average of the underlying assets' characteristics, which serves as $\widetilde{Z}_{k,s,t}$ in Eq. 10.

Macroeconomic Predictors We consider 20 macroeconomic predictors to help predict basis portfolio returns in Eq. 10. Detailed descriptions on the predictors are included in Table D.1. Lin et al. (2014) and Lin et al. (2018) find that macroeconomic variables contains rich information for future corporate bond returns. Our macro predictor set covers two main categories: bond market variables (e.g., treasury bill rate, rating spread) and equity market variables (e.g., S&P 500 index returns, S&P 500 index earnings-to-price ratio).

Factor Models Fama and French (1993) provide a five-factor model (FF5) that tries to explain the cross-sectional variation of both equity and bond returns, including MKT, SMB, HML, TERM, and DEF. [6] FF5 is available for our whole sample period. Bai et al. (2019) propose a four-factor model (BBW4) for corporate bond market, including MKTbond, DRF, CRF, and LRF. [7] BBW4 data starts from July 2004. So, the comparison between BCM and BBW4 is only applicable in recent 16 years.

The beta of each bond is estimated via time-series regression with an intercept. We consider two versions of the beta. The in-sample beta of a bond is estimated with one regression that includes the bond's whole return time series. The out-of-sample beta of a bond on a date is estimated with the past five-year rolling window data.

[6] The monthly returns of MKT, SMB, and HML are downloaded from Kenneth R. French. We also benefit from Amit Goyal for calculating TERM and DEF. TERM is the difference between the monthly long-term government bond return (from Ibbotson Associates) and the one-month treasury bill rate measured at the end of the previous month (from the Center for Research in Security Prices, CRSP). DEF is the difference between the return on a market portfolio of long-term corporate bonds (the Composite portfolio on the corporate bond module of Ibbotson Associates) and the long-term government bond return.

[7] BBW4 is downloaded form Turan G. Bali.

3.2 Bond Risk Premium Decomposition

In-Sample Estimation. Table 2 reports the combination weight values and bootstrap inference results. The first column is the estimation over 45 years from 1976 to 2020. We find that the benchmarks related to rating, maturity, short-term reversal, momentum (12 months), and variance have positive weights. According to the 1000 bootstrap exercises, there are more than 90% chances that these five benchmarks have positive weights. The other benchmarks have almost zero weights and less than 10% chances of positive weights in bootstrap inference.

The second and third columns report the benchmark importance under different economic regimes. We classify the sample into expansion and recession according to the NBER Business Cycle Dating. We find maturity benchmark matters only in expansion. Rating and short-term reversal are persistently strong with more than 15% weights in both regimes, but the former is stronger in recession, and the latter is stronger in expansion. Momentum (12 months) and variance are more important in recession than expansion.

We report the estimation for each five-year window in the remaining nine columns to investigate the time-varying patterns in benchmark weights. Rating is neglected by our model in the 1990s. Maturity is missed in two subsamples, the early 1980s recession and the 2008 global financial crisis, consistent with columns two and three. Short-term reversal is persistently positive over all subsamples. Momentums (6 and 12 months) are important in the early sample but seldom selected after 2000. Downside risk is only positive in the late 1970s and around the 2008 global financial crisis. Given the time-varying fact for subsample analysis, it is necessary to estimate dynamic weights for out-of-sample exercises.

[Insert Table 2 here]

Out-of-Sample Estimation. We estimate the combination weights for each year with the past five-year sample. In Table 3, there are 40 rows for each year from 1981 to 2020. Again, we find clear time-varying patterns in the weights. The out-of-sample weight is important for investment applications, such as constructing a replicating portfolio to hedge the risk of a corporate bond (total R^2 in Eq. 12) and predicting future corporate bond returns (predictive R^2 in Eq. 13 and out-of-sample R^2 in Eq 16).

[Insert Table 3 here]

Alternative Specifications. In addition to the constrained panel regression in Eq. 8, we investigate two alternative specifications to estimate combination weights: LASSO and step-wise selection. We run LASSO with nonlinearity constraint and then re-scale the weights to meet the sum-to-unity constraint. For (forward) step-wise selection, we run linear regression with the two constraints for each regression and use "BIC" as the criteria for model selection. In Table E.1, E.2, E.3, and E.4, we report the alternative results with model selection focus. We find the estimated value of LASSO and step-wise selection are very close to our main result. The selected positive benchmarks in LASSO and step-wise selection are also consistent with our main result. The sparsity pattern seems to result from non-negativity constraint, instead of the LASSO penalty of step-wise selection.

We also consider value-weighted basis portfolio returns for BCM. The combination weights are reported in Table E.5, and E.6. The stylized facts on selected positive benchmarks are still consistent with the main result, the equal-weighted basis portfolio case, except that the size benchmark takes a higher weight in value-weighted specification. Overall, our combination weight estimation is robust to alternative specifications. In empirical applications, we only report for the constrained BCM with equal-weighted basis portfolio return as the main result.

3.3 Asset Pricing Model Performance

In-Sample Pricing Performance. Table 4 reports the in-sample pricing performance of BCM. In the first row panel A, with a sparse weight of 5 non-negative components, BCM explains about 40% of the total variation in individual corporate returns for a large sample from year 1976 to 2020. The performance is persistent over time since the Fama-MacBeth time-series average $\overline{R^2}$ is also about 40% and statistically significant. In the second row, the expansion period performance is close to the whole period, but remember the combination weight is fitted with only the expansion period observations. In the third row, recession has about 5% larger total R^2 than expansion. When we look into five-year sub-periods in the remaining rows of panel A, the performance measure is persistently positive in the range of 27% to 85%, and the Fama-MacBeth version is in the range of 22% to 66%. Comparing different rating groups, we find the pricing performance is robust. The returns of Investment Grade Bonds are more explainable than Non-Investment Grade Bonds.

The total R^2 in panel A takes account of the contemporaneous realizations in basis portfolio returns, while the predictive R^2 in panel B is about the fraction of return variation explained by the conditional expected returns. Although BCM has 40% of total R^2, we find the predictive R^2 is much smaller. The predictive R^2 for the whole sample is less than 1%. The overall predictive R^2 is positive, but not persistent over time. We only find a few subsamples that the Fam-MacBeth $\overline{R^2}$ is statistically significant, e.g., early 1990s, early 2010s, and Non-Investment Grade Bonds in expansion. Luckily, the predictive R^2 is acceptable in the recent decade.

[Insert Table 4 here]

Out-of-Sample Pricing Performance. Table 5 reports the out-of-sample pricing performance of BCM. The combination weights are estimated annually with past five-year data and reported in Table 3. In panel A, the out-of-sample total R^2 is about 35%, which is close to the in-sample counterpart with a slight decrease. We can construct a dynamic replicating portfolio for each bond, and it hedges 35% return variation in the cross section of corporate bond returns. The results are persistently strong for different subsamples.

Panel B shows the out-of-sample predictive R^2, which is essentially a predictive performance measure. The predictive R^2 becomes more than 1% and significantly larger than zero, when we dynamically update the combination weights $\hat{\omega}_k$ and trailing mean $\bar{X}_{i,t-1,k}$ of basis portfolio returns. A positive predictive R^2 means the BCM forecast is more accurate than a naive zero forecast. Looking at five-year subsamples, we find 4 out of 8 periods have significantly positive predictive R^2. The return predictability is concentrated in economic expansion. It is easier to predict the Non-Investment Grade Bonds returns than Investment Grade Bond returns.

[Insert Table 5 here]

Model Comparison. We evaluate the pricing performance of FF5 (MKT, SMB, HML, TERM, and DEF from year 1976 to 2020) (Fama and French, 1993) and BBW4 (MKTbond, DRF, CRF, and LRF from July 2004 to 2020) (Bai et al., 2019) and compare with BCM.

Table 6 reports the in-sample results. FF5 provides positive total R^2 since January 1976 , but its Fama-MacBeth time-series average $\overline{R^2}$ is negative. The total R^2 of BBW4 is statistically significant and close to BCM. But, BBW4 is available in a relatively short period. The predictive R^2 of FF5 is significantly positive after July 2004, while BBW4 is negative. BCM has the largest predictive R^2 among the three.

[Insert Table 6 here]

The out-of-sample comparison is in Table 7. From in-sample to out-of-sample results, the total R^2 drops dramatically for FF5 and BBW4, but BCM only decrease less than 10%. The out-of-sample predictive R^2 of all three models are positive after July 2009, and BCM outperforms FF5 and BBW4.

[Insert Table 7 here]

More details about the performance of FF5 and BBW4 are reported in Table F.1 and F.2. Overall, the BCM gives higher asset pricing performance in individual corporate bond returns than FF5 and BBW4.

3.4 Predicting Returns with BCM

The results above suggest that BCM serves as an asset pricing model very well. An issue of considerable interest is whether we can exploit BCM for predicting future bond returns. The out-of-sample predictive R^2 in Table 5 is actually a predictive performance measure, and it shows the potential of BCM in predicting individual bond returns. Recall that we use the trailing mean of basis portfolio returns as the conditional expected return for basis portfolios $\bar{X}_{i,t-1,k}$. If we have a better prediction for future basis portfolio returns than the trailing mean, we are likely to see even better predictions for individual corporate bond returns. This section provides further evidence of return predictability under BCM framework using both conventional and machine learning methods.

Predicting Basis Portfolio Returns. Referring to Hong et al. (2012); Lin et al. (2014, 2018), we predict the basis portfolio returns with portfolio-level characteristics and macroeconomic variables. We list four predictive models including: Mean Combination Forecast, LASSO, PCA Regression, and Random Forest. All of them outperform the historical average of 20-year window in predicting future basis portfolio returns. Please find the details in Appendix G and Table G.1.

Predicting Individual Bond Returns by BCM. Next, we demonstrate how to generate return forecasts using BCM. In step one, we create the return forecasts for various basis portfolios. In step two, we combine these return forecasts with the dynamic weights in Table 3 to obtain predictions for individual bond returns.

Table 8 panel A reports the out-of-sample performance of the benchmark combination forecast over year 1996 to 2020. Taking LASSO as an example, we have LASSO predictions for various basis portfolios and combine these LASSO forecasts with BCM weights. We then report the out-of-sample R^2_{OOS} of predicting individual bond returns by the weighted combination LASSO forecast, labeled "BCM-LASSO". We find that the historical average forecast of basis portfolios and BCM already gives good predictions for individual corporate bond returns, while Mean Combination Forecast, LASSO, PCA Regression, and Random Forest show substantial out-of-sample predictability. In contrast, FF5 does not show a positive number.

In terms of sub-periods, we find the return predictability is concentrated in expansion (panel B), and is weak in recession (panel C). The predictability is larger in Investment Grade Bonds than Non-Investment Grade Bonds. To accommodate the data availability of BBW4, we report panel D for July 2009 to recent. Overall, the four predictive model forecasts under BCM framework can predict individual corporate bond returns more accurately than historical average and BCM. Among the five BCM forecasts, BCM-RF is the most recommended specification. It is possible to survey more machine learning models to predict basis portfolio returns, but our point is that the BCM framework is valuable in return prediction tasks.

[Insert Table 8 here]

Investment Performance. We construct forecast-implied (quintile) long-short portfolios based on BCM forecasts for individual corporate bond returns. Figure 1 shows the cumulative returns of the sorted portfolios and long-short portfolios. One dollar investment in 1996 grows to about 7 dollars in 2020 for BCM-MEAN and BCM-RF. We find the long-short strategy returns grow exponentially, but have some drawdowns in recession, especially during the 2008 global financial crisis and the 2020 pandemic.

[Insert Figure 1 here]

Table 9 reports the performance measures for these long-short portfolios. We report the average return, α based on FF5, t-statistics for the alpha, and the annualized Sharpe ratio. These positive investment performances are robust for all listed methods, including BCM-AVG. The α's are significantly positive, indicating FF5 cannot explain the long-short strategy returns.

BCM-RF delivers a 66 bp monthly average return, 61 bp alpha on FF5, and 2.05 annualized Sharpe ratio. The Sharpe ratio is even larger, if we only include Investment Grade bonds or only invest during expansion. During recession, the alpha of BCM-RF on FF5 is 83 bp, although the R^2 measure is negative. In panel D, we report alpha controlling BBW4. Still, BCM-RF has a significantly positive alpha of 42 bp, and the Sharpe ratio is 2.13 after July 2009. Overall, the long-short investment strategies generate significant profits and risk-adjusted performance.

[Insert Table 9 here]

4 Conclusion

This paper presents a new asset pricing framework to estimate and decompose the individual asset risk premia. The proposed benchmark combination model (BCM) is related to the linear factor asset pricing model and the basis portfolio benchmark evaluation of Daniel et al. (1997). BCM is a solution to the high-dimensional sort difficulty in Cochrane (2011) using a linear combination of univariate-sorted basis portfolios. We provide a linear model combination framework that is transparent, objective, and economically interpretable. This approach can be easily applied to corporate bond market and other asset classes.

With a no-arbitrage objective, BCM minimizes cross-sectional pricing errors and decomposes the sources of risk premia. We apply the model to corporate bond data and find that credit ratings, maturity, short-term return reversal, momentum (12 months), and variance are five important sources of corporate bond risk premia. In particular, short-term reversal is an under-appreciated characteristic with high explanatory power for corporate bond returns.

We compare BCM with the conventional factor models for pricing and prediction performance. BCM has the advantage of dealing with individual assets that have a short history of data, low signal-to-noise ratio, and nonlinear relations between characteristics and returns. We find evidence that BCM outperforms conventional factor models in pricing individual corporate bond returns. Moreover, BCM generates substantial return predictability for individual corporate bonds.

For future research, BCM is applicable to other assets, such as equity, mutual fund, FX, option, crypto, and so on. The current investigation on BCM is empirical, we also welcome theoretical works on it.

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Figure 1: Long-Short Strategy Returns

This figure shows the cumulative returns plot of the sorted portfolios and long-short strategies. Label 1 to 5 are the low to high portfolios. Label "ls" is the long-short strategy. The shadow area is recession by NBER.

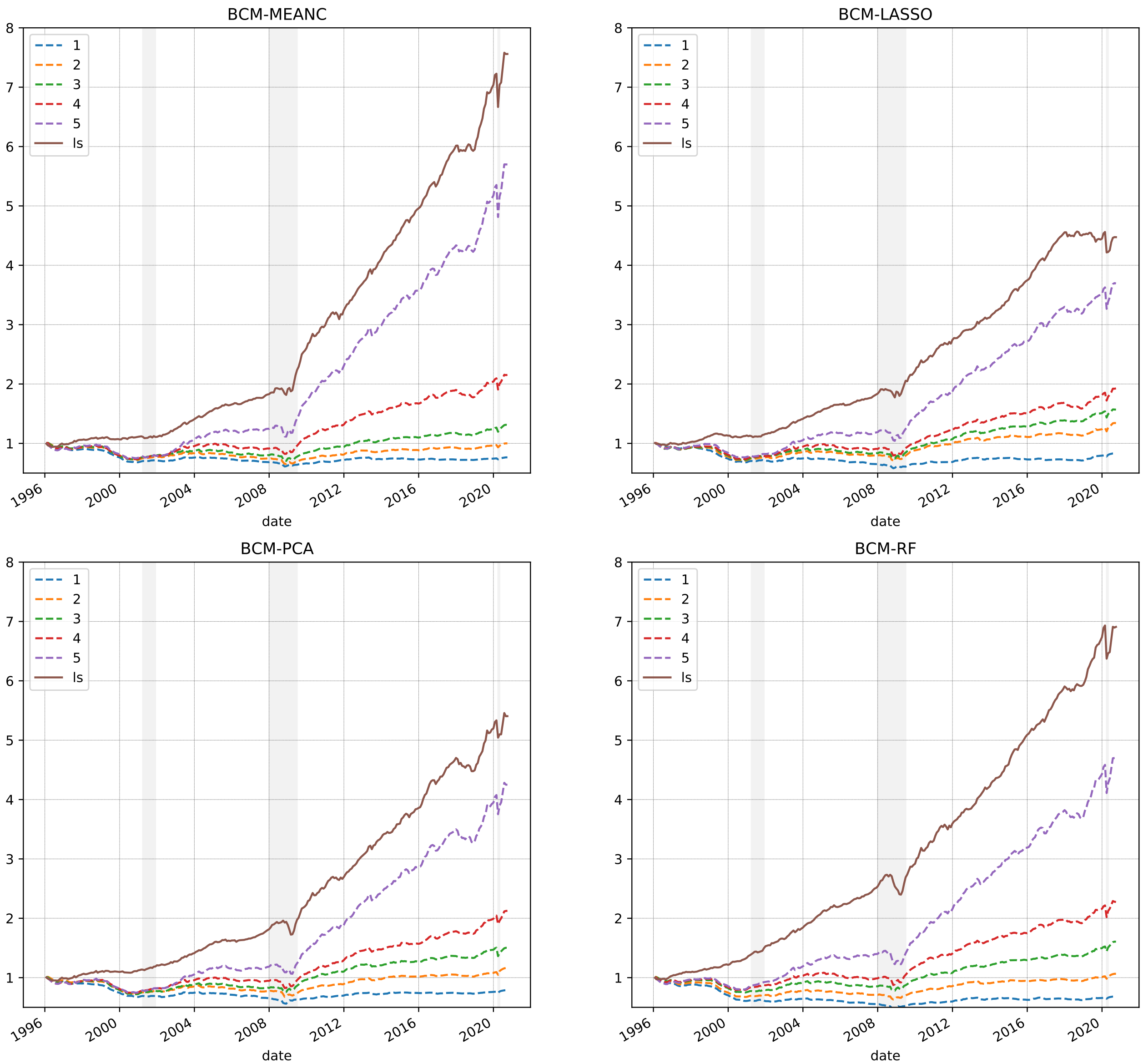


Table 1: Summary Statistics

The sample includes 753,274 monthly return observations of 22,747 unique corporate bonds by 3,620 firms from January 1976 to September 2020. The raw data starts in 1973. However, we require a three-year window to initialize risk characteristics such as β_{term}, β_{smb}, and so on. We report TRACE and NAIC together because they are both transaction-based data, and a large proportion of NAIC observations are covered by TRACE.

Panel A: Descriptive Statstics

	All Databases	Lehman	DataStream	TRACE&NAIC
Bond-month observations	753,274	182,931	20,413	549,930
Start Year	1976	1976	1990	1993
End Year	2020	1998	2008	2020
% of IG	85.23	88.06	77.48	84.49
% of NIG	14.77	11.94	22.52	15.51
Return - mean (%)	0.51	0.78	0.51	0.41
Return - median (%)	0.39	0.69	0.42	0.28
Excess return - mean (%)	0.20	0.19	0.20	0.21
Excess return - median (%)	0.12	0.16	0.12	0.10
Rating - mean	5.60	5.58	7.46	5.53
Rating - median	5	5	7	5
Duration - mean (years)	5.61	5.37	8.91	5.58
Duration - median (years)	4.82	5.01	9.48	4.57
Age - mean (years)	6.37	7.16	6.78	6.09
Age - median (years)	5.03	6.41	6.34	4.39
Amt outst. - mean ($ million)	502	64	186	662
Amt outst. - median ($ million)	130	25	100	200

Panel B: Sample Distribution (%) By Rating & Maturity

	AAA	AA	A	BBB	NIG	All
Maturity						
1	2.04	2.13	5.46	2.77	1.00	13.41
2	1.62	2.03	5.10	2.59	0.92	12.26
3	1.16	1.67	4.26	2.26	0.85	10.21
4	1.16	1.56	4.18	2.12	0.80	9.82
5	0.68	1.00	2.76	1.68	0.71	6.83
6	0.67	0.89	2.62	1.62	0.68	6.48
7	0.51	0.80	2.31	1.48	0.56	5.65
8	0.49	0.77	2.26	1.37	0.51	5.40
9	0.47	0.74	2.20	1.30	0.47	5.19
10	0.13	0.41	0.96	0.80	0.28	2.58
≥ 11	1.73	2.53	7.80	7.52	2.60	22.18
All	10.67	14.54	39.90	25.52	9.38	100.00

Table 2: Weight (%) for Benchmark Combination Model

This table reports the weights (in percentage) in the Benchmark Combination Model. We require two constraints: sum-to-unity and non-negativity. The first column reports the estimation of the whole sample form year 1976 to 2020. The second and third columns are for expansion and recession periods referring the NBER recession indicator. The remaining columns are estimated for each five-year sub-sample. The cell colors indicate the positive frequency of weights by the 1000 bootstrap samples. We categorize the cells into four sets based on the positive frequency, divided by three breakpoints—10%, 50%, and 90%—and color the four sets of cells in the blank, light, medium, and dark backgrounds.

	1976-2020	Expansion	Recession	1976-1980	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2020
Rating	23	16	36	7	20	13	0	0	14	49	17	22
Maturity	24	43	0	34	0	51	37	32	44	0	44	37
Size	0	0	0	0	0	0	0	29	0	0	0	0
Age	0	0	0	0	0	0	0	0	0	0	0	0
Coupon	0	0	0	0	0	0	0	0	0	0	0	0
S-term Rev	28	35	17	16	17	14	35	27	42	18	39	8
Mom 6M	0	0	0	0	5	3	9	0	0	0	0	0
Mom12M	7	3	13	0	16	2	20	0	0	4	0	0
L-term Rev 2Y	0	0	0	2	0	0	0	0	0	0	0	0
L-term Rev 3Y	0	0	0	0	0	0	0	13	0	0	0	0
Variance	18	4	34	35	42	0	0	0	0	18	0	33
Downside Risk	0	0	0	6	0	0	0	0	0	11	0	0
Skewness	0	0	0	0	0	0	0	0	0	0	0	0
Kurtosis	0	0	0	0	0	0	0	0	0	0	0	0
Beta_mktrf	0	0	0	0	0	0	0	0	0	0	0	0
Beta_smb	0	0	0	0	0	0	0	0	0	0	0	0
Beta_hml	0	0	0	0	0	0	0	0	0	0	0	0
Beta_term	0	0	0	0	0	0	0	0	0	0	0	0
Beta_def	0	0	0	0	0	0	0	0	0	0	0	0
Residual Variance	0	0	0	0	0	17	0	0	0	0	0	0
Bootstrap Positive Frequency			[0, 10%)		[10%, 50%)			[50%, 90%)			[90%, 100%]	

Table 3: Out-of-Sample Weight (%) for Benchmark Combination Model

This table reports the out-of-sample weight (in percentage) for the Benchmark Combination Model. There are 40 rows for the 40 years from 1981 to 2020. For each year, we estimate the weights with the past five-year rolling window data, e.g., row 1981 is estimated with data from 1976 to 1980. The format follows Table 2.

	Rating	Maturity	Size	Age	Coupon	S-term Rev	Mom 6M	Mom12M	L-term Rev 2Y	L-term Rev 3Y	Variance	Downside Risk	Skewness	Kurtosis	Beta_mktrf	Beta_smb	Beta_hml	Beta_term	Beta_def	Residual Variance
1981	7	34	0	0	0	16	0	0	2	0	35	6	0	0	0	0	0	0	0	0
1982	1	27	0	0	0	21	11	0	1	0	40	0	0	0	0	0	0	0	0	0
1983	3	18	0	0	0	16	2	7	2	1	52	0	0	0	0	0	0	0	0	0
1984	4	12	0	0	0	17	3	7	2	0	55	0	0	0	0	0	0	0	0	0
1985	12	0	0	0	0	21	4	19	0	0	44	0	0	0	0	0	0	0	0	0
1986	20	0	0	0	0	17	5	16	0	0	42	0	0	0	0	0	0	0	0	0
1987	28	0	0	0	0	18	2	20	0	0	32	0	0	0	0	0	0	0	0	0
1988	34	0	0	0	0	20	17	18	0	0	11	0	0	0	0	0	0	0	0	0
1989	39	0	0	0	0	20	22	17	0	0	1	0	0	0	0	0	0	0	0	0
1990	37	42	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	9
1991	13	51	0	0	0	14	3	2	0	0	0	0	0	0	0	0	0	0	0	17
1992	17	56	0	0	0	6	0	6	0	0	0	0	0	0	0	0	0	0	0	15
1993	0	36	0	0	42	3	0	2	0	0	0	0	0	0	0	0	0	0	0	17
1994	0	45	0	0	40	4	0	0	0	0	0	0	0	0	0	0	0	0	0	10
1995	0	41	0	0	4	34	0	18	0	0	0	0	0	0	0	0	0	0	3	0
1996	0	37	0	0	0	35	9	20	0	0	0	0	0	0	0	0	0	0	0	0
1997	0	24	0	0	0	32	21	8	5	10	0	0	0	0	0	0	0	0	0	0
1998	0	28	0	0	0	29	11	14	0	11	0	0	0	0	0	7	0	0	0	0
1999	0	26	4	0	0	34	8	10	0	10	0	0	0	0	0	7	0	0	0	0
2000	0	29	14	0	0	30	7	3	0	12	0	0	0	0	0	6	0	0	0	0
2001	0	32	29	0	0	27	0	0	0	13	0	0	0	0	0	0	0	0	0	0
2002	0	31	42	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	0	22	37	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	5	39	17	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	13	44	1	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	14	44	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	14	47	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2008	17	54	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	53	31	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2010	48	0	0	0	0	18	0	4	0	0	19	10	0	0	0	0	0	0	0	0
2011	49	0	0	0	0	18	0	4	0	0	18	11	0	0	0	0	0	0	0	0
2012	49	0	0	0	0	22	0	4	0	0	14	11	0	0	0	0	0	0	0	0
2013	47	0	0	0	0	21	0	7	0	0	13	11	0	0	0	0	0	0	0	0
2014	21	0	0	0	0	27	0	11	0	0	10	31	0	0	0	0	0	0	0	0
2015	28	37	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2016	17	44	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2017	16	63	0	0	0	17	0	5	0	0	0	0	0	0	0	0	0	0	0	0
2018	16	66	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2019	12	68	0	0	0	19	0	0	0	0	1	0	0	0	0	0	0	0	0	0
2020	11	68	0	0	0	18	0	0	0	0	3	0	0	0	0	0	0	0	0	0

Bootstrap Positive Frequency: [0, 10%) [10%, 50%) [50%, 90%) [90%, 100%]

Table 4: Pricing Performance for Individual Corporate Bonds (In-Sample Result)

This table reports the (in-sample) pricing performance of BCM for individual corporate bond returns. The combination weights are reported in Table 2. The first three rows are based on the whole sample, the expansion period, and the recession period. The remaining rows are for each five-year window. Panel A reports the performance for the total R^2 in Eq. 12. In the columns, we consider the whole sample, the Investment Grade Bonds, and the Non-Investment Grade Bonds. Panel B reports the predictive R^2 in Eq. 13, and we use the unconditional average of basis portfolio returns as the $\bar{X}_{i,t-1,k}$. The R^2 columns report the aggregated pricing performance, pooling all bonds and periods. FM-$\overline{R^2}$ reports the time-series average of $\{R_t^2\}_{t=1}^T$, more details in Section 2.8. We also report the Fama-MacBeth t-test for FM-$\overline{R^2}$, where the signs ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	All Bond		Investment Grade Bond		Non-Investment Grade Bond	
Time Range	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
Panel A: Total R^2 %						
1976-2020	39.79	39.54***	41.82	40.95***	29.78	24.81***
Expansion	38.43	39.40***	40.71	40.98***	25.45	22.54***
Recession	43.26	42.65***	44.94	42.55***	36.72	34.47***
1976-1980	85.33	66.80***	87.87	69.10***	40.63	17.72***
1981-1985	76.68	61.51***	78.62	63.54***	44.49	36.42***
1986-1990	59.25	47.74***	65.70	53.18***	32.06	23.33***
1991-1995	43.07	48.60***	45.46	48.84***	26.69	31.56***
1996-2000	32.09	26.48***	32.67	26.79***	25.93	21.09***
2001-2005	27.52	23.49***	29.76	25.09***	17.92	14.06***
2006-2010	28.25	22.70***	25.93	21.83***	35.02	21.24***
2011-2015	32.98	27.90***	33.51	27.87***	30.11	23.99***
2016-2020	52.76	33.95***	52.15	34.79***	55.29	22.55***
Panel B: Predictive R^2 %						
1976-2020	0.67	1.29	0.54	0.99	1.32	2.38***
Expansion	0.85	1.41*	0.63	1.10	2.13	2.40***
Recession	0.85	2.26	1.13	2.51	-0.26	1.66
1976-1980	0.15	-6.25	0.24	-6.59	-1.52	-7.54
1981-1985	1.36	-2.91	1.25	-3.27	3.10	-0.81
1986-1990	3.19	-4.05	3.10	-6.91	3.60	1.71
1991-1995	0.80	6.11***	0.57	6.10**	2.32	6.34***
1996-2000	5.48	0.52	5.53	0.41	5.01	0.25
2001-2005	3.52	3.16	3.41	3.08	3.99	3.16*
2006-2010	0.73	-0.49	0.69	-0.69	0.86	0.42
2011-2015	7.58	7.00***	7.29	6.52***	9.11	8.02***
2016-2020	4.58	3.64	4.94	3.28	3.10	5.89

Table 5: Pricing Performance for Individual Corporate Bonds (Out-of-Sample Result)

This table reports the (out-of-sample) pricing performance of BCM for individual corporate bond returns. The combination weights are updated annually and reported in Table 3. To calculate the out-of-sample predictive R^2, we use the trailing average of basis portfolio returns as the $\bar{X}_{i,t-1,k}$ in Eq. 13. Other format follows Table 4.

	All Bond		Investment Grade Bond		Non-Investment Grade Bond	
Time Range	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
Panel A: Total R^2 %						
1981-2020	35.12	35.96***	36.62	37.06***	28.26	23.48***
Expansion	34.51	35.64***	36.32	36.87***	24.78	22.75***
Recession	36.27	38.55***	37.25	38.62***	32.87	29.40***
1981-1985	75.82	60.17***	77.93	62.52***	40.72	31.66***
1986-1990	57.89	47.23***	63.57	51.77***	33.92	26.60***
1991-1995	41.74	48.05***	44.14	47.73***	25.30	30.15***
1996-2000	31.46	25.82***	32.13	26.18***	24.29	19.51***
2001-2005	26.82	23.41***	29.11	25.12***	17.02	13.70***
2006-2010	26.50	22.64***	25.16	22.42***	30.40	18.68***
2011-2015	31.16	26.46***	30.80	25.70***	33.07	26.36***
2016-2020	51.96	34.20***	51.80	35.36***	52.59	21.17***
Panel B: Predictive R^2 %						
1981-2020	0.19	1.06*	0.04	0.87	0.90	2.18***
Expansion	0.65	1.28*	0.43	1.02	1.89	2.52***
Recession	-0.43	-0.72	-0.49	-0.39	-0.21	-0.55
1981-1985	-2.46	-2.41	-2.56	-2.56	-0.98	-0.85
1986-1990	0.45	-3.02	0.20	-3.87	2.01	1.28
1991-1995	0.17	5.35***	-0.51	5.24**	4.79	6.40***
1996-2000	-2.17	-1.65	-2.21	-1.65	-1.72	-1.35
2001-2005	0.89	1.10**	0.88	1.12**	0.94	0.99**
2006-2010	0.39	0.54	0.32	0.39	0.62	1.13*
2011-2015	3.59	4.09***	3.33	3.78***	4.99	5.02***
2016-2020	3.05	4.63**	3.36	4.61**	1.76	4.93***

Table 6: Comparing BCM and Factor Model (In-Sample Result)

The expression "In-sample" indicates the combination weights of BCM and beta's of FF5 and BBW4 are estimated with whole sample data. The in-sample weight of BCM is reported in the "1976-2020" column of Table 2. The FF5 denotes the five-factor model in Fama and French (1993) and the five factors are MKT, SMB, HML, TERM, and DEF from January 1976 to September 2020. The BBW4 denotes the factor model in Bai et al. (2019) and the four factors are MKTbond, DRF, CRF, and LRF from July 2004 to September 2020. The in-sample FF5 data covers January 1976 to September 2020, and the in-sample BBW data covers July 2004 to September 2020. Format follows Table 4.

		All Bond		Investment Grade Bond		Non-Investment Grade Bond	
Time Range	Model	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
		Panel A: Total R^2 %					
1976 Jan-	BCM	39.79	39.54***	41.82	40.95***	29.78	24.81***
	FF5	13.72	-18.31	11.51	-18.16	24.58	-13.61
2004 Jul-	BCM	30.84	27.69***	30.35	27.97***	32.47	21.80***
	FF5	21.50	-1.72	18.58	-2.51	31.18	-2.89
	BBW4	38.75	20.70***	39.53	21.64***	36.18	12.22***
		Panel B: Predictive R^2 %					
1976 Jan-	BCM	0.67	1.29	0.54	0.99	1.32	2.38***
	FF5	-0.41	-1.48	-0.51	-0.66	0.11	-1.59
2004 Jul-	BCM	1.41	3.14***	1.48	3.00***	1.18	3.69***
	FF5	0.73	1.74***	0.64	1.47***	1.03	2.82***
	BBW4	-0.59	-1.82	-0.81	-1.96	0.27	-1.93

Table 7: Comparing BCM and Factor Model (Out-of-Sample Result)

The expression "Out-of-sample" indicates the combination weights of BCM and beta's of factor models are updated dynamically with a five-year rolling window. So, the out-of-sample data starts five years later than the in-sample data in Table 6. The out-of-sample weight of BCM is in of Table 3. The FF5 denotes the five-factor model in Fama and French (1993) and the five factors are MKT, SMB, HML, TERM, and DEF. The BBW4 denotes the factor model in Bai et al. (2019) and the four factors are MKTbond, DRF, CRF, and LRF. Format follows Table 4.

		All Bond		Investment Grade Bond		Non-Investment Grade Bond	
Time Range	Model	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
Panel A: Total R^2 %							
1981 Jan-	BCM	35.12	35.96***	36.62	37.06***	28.26	23.48***
	FF5	-13.94	-45.18	-13.17	-44.87	-17.41	-60.91
2009 Jul-	BCM	37.28	29.72***	36.33	29.51***	40.95	24.80***
	FF5	-21.31	-25.20	-14.82	-19.06	-46.33	-61.54
	BBW4	15.29	9.17***	19.18	13.15***	0.30	-19.01
Panel B: Predictive R^2 %							
1981 Jan-	BCM	0.19	1.06	0.04	0.87	0.90	2.18***
	FF5	-1.30	-3.04	-1.47	-4.03	-0.55	-0.36
2009 Jul-	BCM	3.13	4.14***	3.04	3.94***	3.50	4.82***
	FF5	1.73	2.51***	1.76	2.31***	1.63	2.68
	BBW4	4.05	1.36	3.58	1.45	5.88	-1.88

Table 8: Predicting Individual Bond Returns with BCM Forecast

This table reports out-of-sample R^2_{OOS} (%) of predicting individual corporate bond returns using the BCM framework combined with five predictive models. We provide four panels for different periods, panel A for the whole out-of-sample period from Jan 1996 to Sep 2020, panel B for the expansion months, panel C for the recession months, and panel D for Jul 2009 and afterward to accommodate the availability of BBW4 data. The BCM-AVG forecast combines the twenty-year rolling window average of basis portfolio returns with the five-year rolling window BCM weight in Table 3. Similarly, we combine the Mean Combination (LASSO, PCA, RF) forecast with BCM weights and get BCM-MEANC (-LASSO, -PCA, -RF) forecasts for individual bond returns. The forecasts for basis portfolios are based on past twenty-year rolling window training model. The row of FF5 is the forecast given by the five-factor model, with a five-year rolling window beta and a twenty-year rolling window average factor return. The row of BBW4 is the forecast given by the BBW four-factor model, with a five-year rolling window beta and expanding window average factor return. Format follows Table 4.

	All Bond		IG Bond		NIG Bond	
Model	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
Panel A: Prediction Period 1996 Jan - 2020 Sep						
BCM-AVG	0.29	0.80***	0.34	0.94	0.06	0.20
BCM-MEANC	1.08	1.50***	1.08	1.61	1.07	0.86**
BCM-LASSO	3.83	2.62***	3.57	2.67***	4.86	1.79*
BCM-PCA	3.73	2.30**	3.22	2.19**	5.83	1.78
BCM-RF	3.40	3.43***	3.60	3.57***	2.61	2.13**
FF5	-0.69	-1.68	-0.85	-1.75	-0.02	-0.88
Panel B: Expansion						
BCM-AVG	0.38	0.87***	0.47	1.03***	-0.07	0.21
BCM-MEANC	1.37	1.65***	1.43	1.78***	1.03	0.92**
BCM-LASSO	4.27	2.84***	4.31	2.95***	4.02	1.74
BCM-PCA	4.97	2.68***	4.82	2.65***	5.69	1.84
BCM-RF	5.04	3.82***	5.35	3.99***	3.47	2.32**
FF5	-1.20	-1.83	-1.41	-1.94	-0.12	-0.87
Panel C: Recession						
BCM-AVG	0.13	0.15**	0.10	0.16	0.22	0.13
BCM-MEANC	0.56	0.04	0.37	-0.05	1.10	0.35
BCM-LASSO	3.04	0.50	2.08	-0.01	5.81	2.21
BCM-PCA	1.52	-1.31	-0.02	-2.21	5.98	1.22
BCM-RF	0.47	-0.32	0.07	-0.47	1.63	0.24
FF5	0.22	-0.21	0.27	0.03	0.10	-1.01
Panel D: Prediction Period 2009 Jul - 2020 Sep (for BBW4 data)						
BCM-AVG	0.69	1.37***	0.96	1.67***	-0.37	-0.40
BCM-MEANC	1.97	2.09***	2.05	2.33***	1.65	0.41
BCM-LASSO	4.77	1.77	4.61	2.00	5.39	-0.15
BCM-PCA	4.81	1.29	3.81	1.11	8.70	0.89
BCM-RF	4.49	3.17***	4.65	3.39***	3.87	1.23
BBW4	3.36	1.19	2.89	1.33	5.23	-0.89
FF5	0.51	-1.35	0.27	-1.47	1.46	-0.99

Table 9: Forecast-Implied Long-Short Strategy Performance

This table reports the performance for the forecast-implied quintile long-short strategies. The performance measures include average excess returns (%), alphas (%) on a factor model (use FF5 for panel A, B, and C, use BBW4 for panel D), t-statistics for the alpha, and the annualized Sharpe ratio. The signs ***, **, and * indicate the significance of alphas at the 1%, 5%, and 10% level, respectively.

	All Bond			IG Bond			NIG Bond		
Model	Avg.Ret	α	SR	Avg.Ret.	α	SR	Avg.Ret.	α	SR
Panel A: Prediction Period 1996 Jan - 2020 Sep									
BCM-AVG	0.67	0.58***	1.89	0.66	0.60***	1.95	0.57	0.47***	1.41
BCM-MEANC	0.69	0.59***	1.73	0.69	0.61***	1.85	0.56	0.49***	1.29
BCM-LASSO	0.51	0.44***	1.55	0.51	0.47***	1.69	0.40	0.33***	1.01
BCM-PCA	0.58	0.53***	1.60	0.52	0.49***	1.56	0.30	0.26***	0.63
BCM-RF	0.66	0.61***	2.05	0.70	0.67***	2.36	0.56	0.52***	1.53
Panel B: Expansion									
BCM-AVG	0.69	0.61***	2.38	0.67	0.62***	2.39	0.59	0.49***	1.84
BCM-MEANC	0.70	0.61***	2.27	0.68	0.62***	2.28	0.58	0.49***	1.74
BCM-LASSO	0.54	0.50***	2.15	0.52	0.51***	2.12	0.40	0.37***	1.29
BCM-PCA	0.60	0.54***	2.00	0.57	0.54***	1.98	0.44	0.39***	1.36
BCM-RF	0.70	0.68***	2.93	0.71	0.71***	2.98	0.57	0.52***	2.04
Panel C: Recession									
BCM-AVG	0.43	0.26	0.59	0.53	0.23	0.79	0.46	0.78	0.51
BCM-MEANC	0.67	0.93*	0.74	0.79	0.85**	0.99	0.37	1.01	0.38
BCM-LASSO	0.24	0.46	0.32	0.39	0.47	0.63	0.39	0.71	0.45
BCM-PCA	0.33	0.85**	0.46	0.05	0.50	0.08	-1.09	-0.35	-0.99
BCM-RF	0.25	0.83**	0.33	0.53	0.96***	0.85	0.47	0.84	0.56
Panel D: Prediction Period 2009 Jul - 2020 Sep (for BBW4 data)									
BCM-AVG	0.92	0.49***	2.43	0.88	0.48***	2.54	0.77	0.38***	1.92
BCM-MEANC	0.92	0.47***	2.29	0.88	0.45***	2.38	0.77	0.41***	1.90
BCM-LASSO	0.58	0.32***	1.77	0.57	0.38***	1.97	0.39	0.23**	1.09
BCM-PCA	0.76	0.35***	2.15	0.70	0.36***	2.24	0.50	0.22**	1.31
BCM-RF	0.71	0.42***	2.13	0.70	0.42***	2.24	0.69	0.42***	1.94

Appendices

A Simulation

For our empirical data, there are extensive nonlinear relations between asset characteristics and expected return, as demonstrated in Figure A.1. This section provides simulation experiments to show that benchmark models capture the nonlinear relations between asset characteristics and expected return in asset pricing. However, the characteristic-based factors (long-short portfolios) do not.

Assume we have $N = 1000$ assets, $T = 300$ time periods, one factor with normal distribution $f_t \sim \mathcal{N}(\mu = 1\%, \sigma^2 = 1\%)$, and one characteristic with uniform distribution in each time period $z_{i,t} \sim \mathcal{U}(-1, 1)$. [8] Other parameters are $a = 0.005, b = 0.5, \mu = 0.005, \sigma = 0.005, \epsilon_{i,t} \sim$ i.i.d. $\mathcal{N}(0, \sigma^2)$. We consider six cases of the data generating process.

- (L) Linear relation between characteristics and expected returns, without factor structure.

  This formulation follows the data generating process of Eq. 5 in Daniel and Titman (1997), which assume expected returns are a function of the observable asset characteristics. We extend the linear assumption between characteristics and expected returns to nonlinear relations in cases U and S.

$$r_{i,t} = az_{i,t-1} + \mu + \epsilon_{i,t} \tag{19}$$

- (U) U-shape relation between characteristics and expected returns, without factor structure.

$$r_{i,t} = az^2_{i,t-1} + \mu + \epsilon_{i,t} \tag{20}$$

- (S) Square-root relation between characteristics and expected returns, without factor structure.

$$r_{i,t} = a(z_{i,t-1} + 1)^{(1/2)} + \mu + \epsilon_{i,t} \tag{21}$$

[8] We assume there is only one factor and one characteristic for demonstration, the study can be extended to multiple factors and characteristics.

- (LF) Linear relation between characteristics and expected returns, with a factor.

  This formulation follows the literature of factor model with conditional beta, such as Rosenberg (1974); Avramov and Chordia (2006). We extend the linear assumption between characteristics and beta's to nonlinear relations in cases UF and SF. In simulation, we estimate the asset beta via time-series regression, agnostic to the conditional relation between characteristics and beta's.

$$\beta_{i,t} = b(z_{i,t-1} + 1) \tag{22}$$

$$r_{i,t} = \beta_{i,t} f_t + \epsilon_{i,t} \tag{23}$$

- (UF) U-shape relation between characteristics and expected returns, with a factor.

$$\beta_{i,t} = b z_{i,t-1}^2 \tag{24}$$

$$r_{i,t} = \beta_{i,t} f_t + \epsilon_{i,t} \tag{25}$$

- (SF) Square-root relation between characteristics and expected returns, with a factor.

$$\beta_{i,t} = b(z_{i,t-1} + 1)^{(1/2)} \tag{26}$$

$$r_{i,t} = \beta_{i,t} f_t + \epsilon_{i,t} \tag{27}$$

For each case, we sort the individual assets into five portfolios based on their characteristic. A long-short factor is simulated as longing the top and shorting the bottom. We report the expected returns of the sorted portfolios and factors in Figure A.2, which clearly shows U-shape, square-root, and linear relations. Notably, the long-short factors don't earn significantly positive returns for the cases (U) and (UF).

The long-short factors can price the assets. In comparison, we use the sorted portfolios as benchmarks to price the assets. In Table A.1, we report the total R^2 and predictive R^2 for the benchmark model and long-short factor model, where we sort the assets into five portfolios. The benchmark model gives positive numbers for cases without a factor structure (U,S, and L), but the factor model does not. For the conditional factor model cases (LF and SF), the factor model gives good results, and so does the benchmark model in total R^2, but the benchmark model is relatively weaker in predictive R^2. The factor model fails dramatically for the conditional factor model case (UF), but the benchmark model is still robust. So, the long-short factor model works only when there is a factor structure, and the relationship between beta's and characteristics is linear. The factor model fails if there is no factor structure or the relations between characteristics and beta's is far from linear, such as a U-shape. Luckily, the benchmark model performs well under the six data generating processes, robust to the factor structure and nonlinearity.

What if we sort into ten portfolios instead of five? In Figure A.3, we report the expected returns of the sorted portfolios and factors. In Table A.2, we report the total R^2 and predictive R^2 for benchmark model (ten sorted portfolios) and long-short factor model, where we sort the assets into ten portfolios. We find the performance of ten-portfolio benchmark model is similar to the five-portfolio benchmark model in Table A.1.

The simulation study assumes a balanced panel data structure. In other words, there is a complete time series for each asset. However, the empirical corporate bond data is unbalanced, making beta estimation even more difficult for factor models. In this sense, benchmark models have a higher chance of outperforming factor models.

Figure A.1: Expected Excess Returns of Sorted Portfolios in Empirical Data

For each characteristic, we sort the cross section of corporate bonds into five portfolios and re-balance monthly over the 45-year sample from 1976 to 2020. We report the expected excess returns (%) for each portfolio. The relation between the characteristics and returns seems linear, e.g., TMT. However, there are also nonlinear relations, e.g., MOM1M, MOM36M, and VAR.

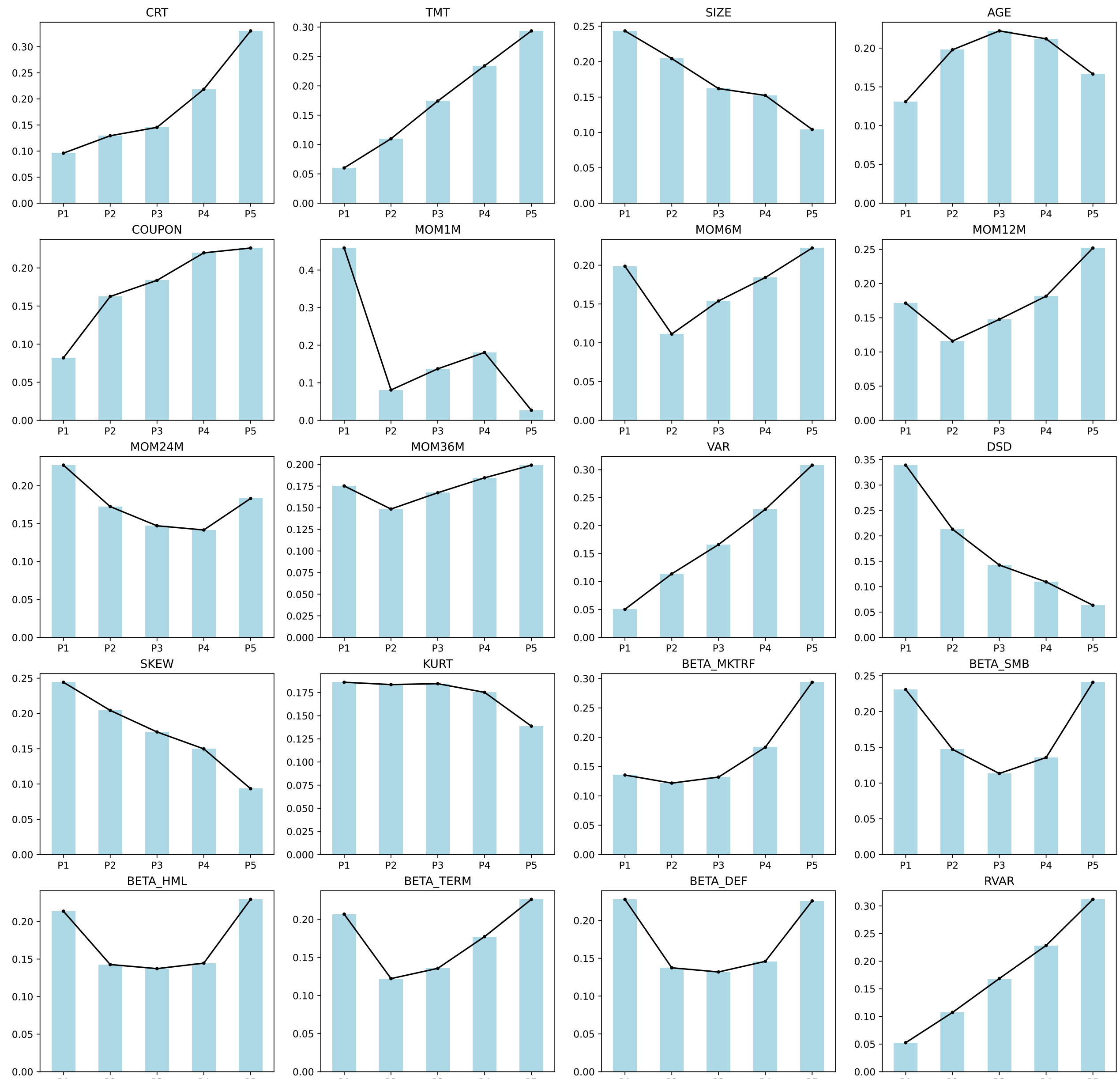
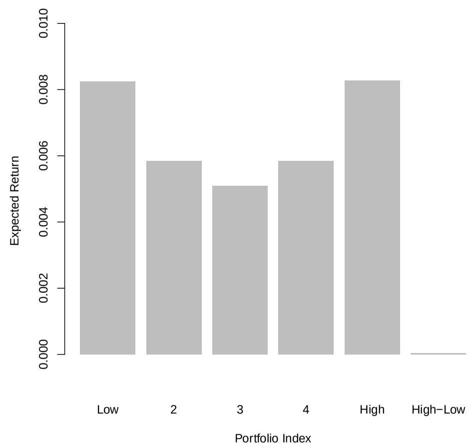
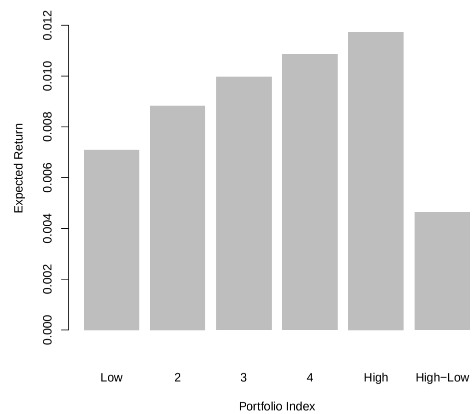


Figure A.2: Expected Returns of Sorted Portfolios and Factors in Simulation, Five-Portfolio Case

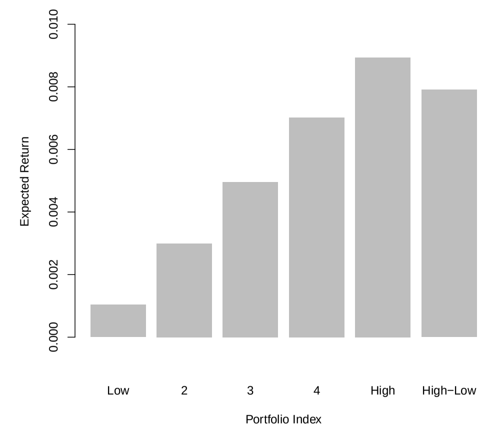
This figure shows the expected returns of the sorted portfolios and long-short factors in simulation.



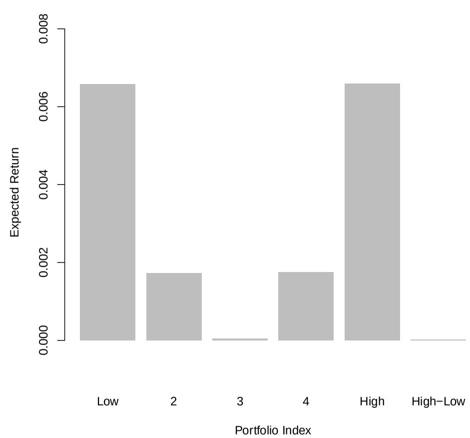
(a) U



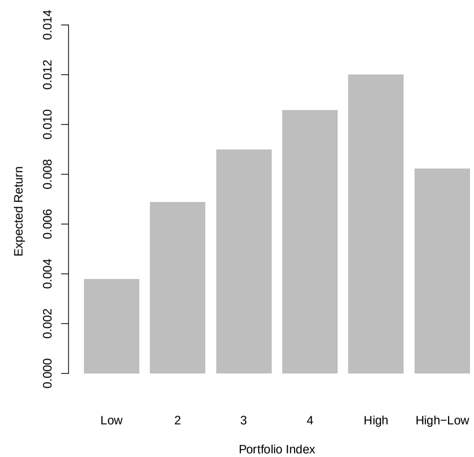
(b) S



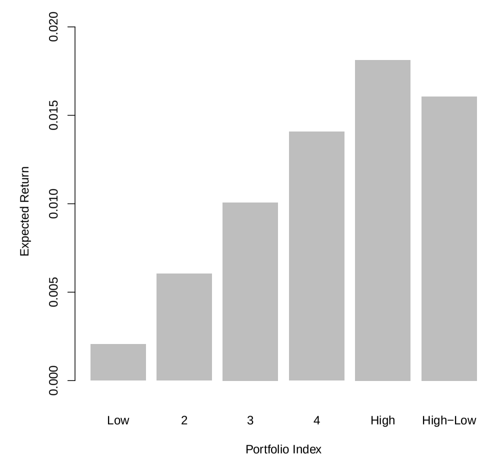
(c) L



(d) UF



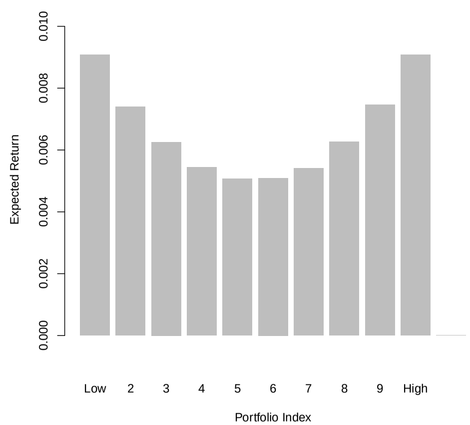
(e) SF



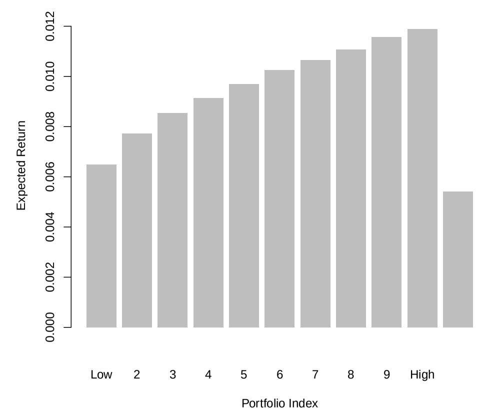
(f) LF

Figure A.3: Expected Returns of Sorted Portfolios and Factors in Simulation, Ten-Portfolio Case

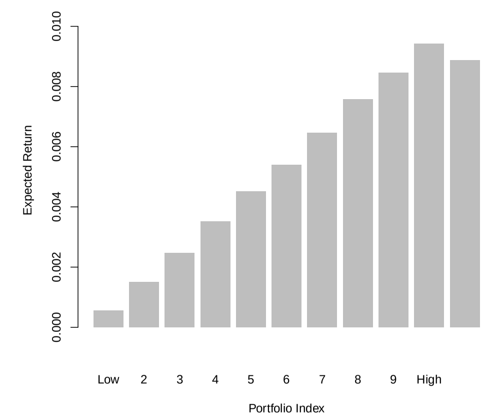
This figure shows the expected returns of the sorted portfolios and long-short factors in simulation.



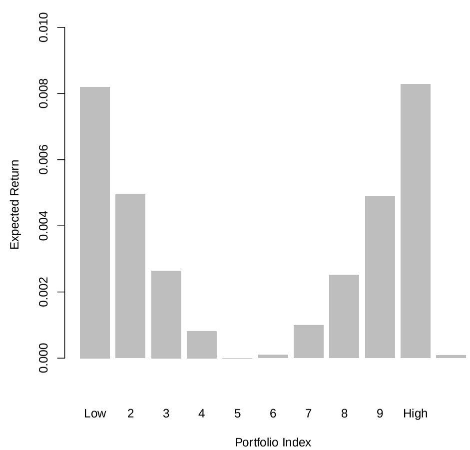
(a) U



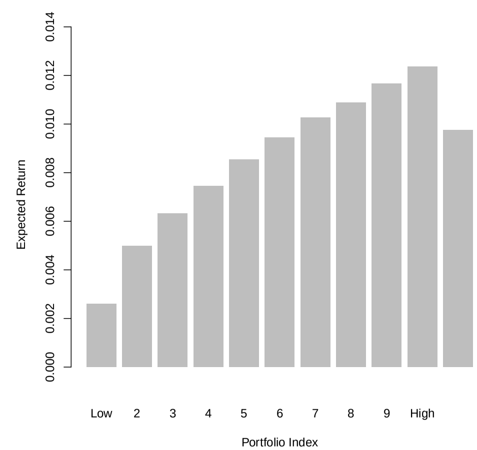
(b) S



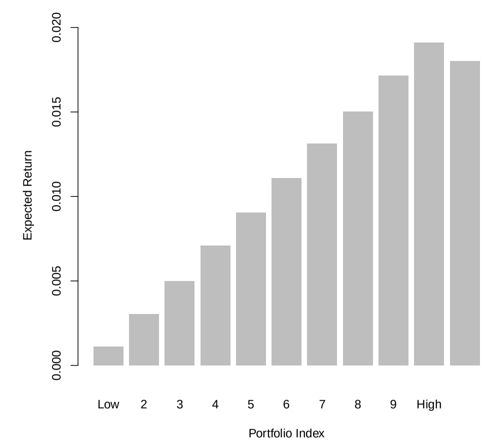
(c) L



(d) UF



(e) SF



(f) LF

Table A.1: Asset Pricing Performance for Simulation, Five-Portfolio Case

This table shows the total R^2 and predictive R^2 of benchmark pricing model and long-short factor based pricing model.

	Benchmark		Factor	
	Total R^2 %	Predictive R^2 %	Total R^2 %	Predictive R^2 %
U	31.72	28.96	0.29	0.00
S	49.40	46.54	-1.71	-1.93
L	24.98	12.90	-10.98	-11.29
UF	26.04	2.70	0.32	-0.04
SF	63.63	22.83	63.61	28.90
LF	71.47	19.36	71.94	37.54

Table A.2: Asset Pricing Performance for Simulation, Ten-Portfolio Case

This table shows the total R^2 and predictive R^2 of benchmark pricing model and long-short factor based pricing model.

	Benchmark		Factor	
	Total R^2 %	Predictive R^2 %	Total R^2 %	Predictive R^2 %
U	32.30	28.70	0.30	0.00
S	49.71	46.48	-0.96	-1.19
L	25.54	12.70	-6.75	-7.07
UF	28.26	1.68	0.25	-0.05
SF	64.13	22.71	63.40	28.91
LF	72.17	19.10	71.88	37.54

B High-Dimensional Sorting Difficulty

This section demonstrates the high-dimensional sort difficulty with the real data in Table B.1. We do independent quintile sorting on maturity and rating, then report the average number of bonds in each sorting bucket. We repeat the process on maturity and downside risk. For rating and maturity, the number of bonds in each bucket is no less than 30 over the 25 years. However, there are a few buckets with less than 10 bonds for maturity and downside risk. These buckets are small portfolios that are not well-diversified. So, the high-dimensional sort difficulty is salient when characteristics are correlated.

Table B.1: The Number of Observations by Buckets for Bivariate Sorts

This table reports the monthly average number of observations in each bucket for independent bivariate sorts from 1996 to 2020. We sort individual corporate bonds by credit rating, maturity, and downside risk into five buckets. The top table shows the number of observations for rating and maturity sorts, and the bottom table shows the bivariate sorts on maturity and downside risk.

		Maturity					
		1	2	3	4	5	All
Rating	AAA	60	52	48	39	34	233
	AA	62	62	53	46	37	260
	A	151	151	139	131	126	697
	BBB	80	83	96	122	139	520
	JUNK	31	36	48	46	48	210
	ALL	384	384	384	384	384	1920
Downside risk	1	18	29	53	85	200	386
	2	19	37	81	114	135	386
	3	38	71	111	122	43	385
	4	82	135	108	56	5	386
	5	228	112	30	6	1	378
	ALL	384	384	384	384	384	1920

C Introduction to Predictive Models

This section introduce the predictive models $g(\cdot)$ used to forecast basis portfolio returns in Eq. 10. And we re-type the essential part as:

$$E_t(R_{k,s,t+1}) = g_{k,s}(\widetilde{Z}_{k,s,t}, x_t).$$

The expected return of basis portfolio $R_{k,s,t+1}$ is a function of the portfolio characteristic $\widetilde{Z}_{k,s,t}$ and the macroeconomic predictor x_t, where k is for characteristic, s is for sorting index, and t is for time. The portfolio characteristic $\widetilde{Z}_{k,s,t}$ is the equal-weighted average of the characteristic of underlying individual bonds in that portfolio, and the macroeconomic predictor x_t is observable.

For each basis portfolio k, s, we fit a time-series predictive model for it and update the model on an annual basis. For simplicity, we omit the subscript k and s, use P of dimension J to denote the joint set of predictors $\widetilde{Z}_{k,s,t}$ and x_t, and re-write the time-series predictive model as:

$$E_t(R_{t+1}) = g(P_t). \tag{28}$$

The first functional form we can consider is (multiple) linear regression, which assumes a linear relationship between returns and predictors.

$$R_{t+1} = g(P_t; \theta) + \varepsilon_{t+1} = P_t^{\intercal}\theta + \varepsilon_{t+1}. \tag{29}$$

The problem can be solved by minimizing the sum of squared errors $\mathcal{L}(\theta)$ via any optimization tool or analytical solution of OLS.

$$\mathcal{L}(\theta) = \frac{1}{T}\sum_{t=1}^{T}\left(R_{t+1} - g\left(P_t; \theta\right)\right)^2. \tag{30}$$

However, linear regression doesn't give acceptable predictive performance in the literature (Welch and Goyal, 2008; Lin et al., 2014; Gu et al., 2020; Bali et al., 2020). Historical average, forecast combination, and machine learning models arise to predict returns quite well. We describe five predictive models of our interest in the following subsections.

C.1 Machine Learning Models

C.1.1 Least Absolute Shrinkage and Selection Operator

The failure of the linear regression model is by large because of the high dimension of the predictors and overfitting. LASSO adds a penalty term on the loss function $\mathcal{L}(\theta)$ in Eq. 30 and we have:

$$\mathcal{L}(\theta; \cdot) = \frac{1}{T} \sum_{t=1}^{T} \left(R_{t+1} - g\left(P_t; \theta\right)\right)^2 + \lambda \sum_{j=1}^{J} |\theta_j| \,. \tag{31}$$

The loss function penalizes the sum of the absolute value of the coefficients in favor of a parsimonious specification to avoid overfitting. As a result, some coefficients will be penalized to zero. The goal of using LASSO is to get a better out-of-sample prediction than linear regression. The hyperparameter λ controls for the amount of penalty, which is chosen by cross-validation described in Section C.1.4.

C.1.2 Principal Component Regression

PCR projects the high-dimensional predictors to a small number of uncorrelated principal components. This is a brilliant way to deal with the high correlation and high dimension in the predictor set. The number of principal components denoted as J' is a hyperparameter, which is smaller than J.

In the first step, we recursively estimate the principal component weight matrix $\Omega_{J'}$ of dimension $J \times J'$. The principal components are deemed to retain essential information of the predictor set in the dimension reduction process. This step is unsupervised machine learning. For the j'-th column of $\Omega_{J'}$, we solve it as

$$w_{j'} = \arg\max_{w} \operatorname{Var}(P_t w), \quad \text{s.t. } w'w = 1, \quad \operatorname{Cov}\left(P_t w, P_t w_l\right) = 0, l = 1, 2, \ldots, j' - 1. \tag{32}$$

In the second step, we run predictive linear regression with the principal components. This step is supervised machine learning.

$$R_{t+1} = (P_t \Omega_{J'})^{\intercal} \theta_{J'} + \tilde{\varepsilon}_{t+1}. \tag{33}$$

C.1.3 Random Forest

Tree models are flexible for nonlinear and interactive functional form, unlike the linear models listed above. A single tree clusters the observations into non-overlapping groups or leaves. Each leaf has a parameter that is the tree prediction for the dependent variable of the observations in that leaf. Assume we have L leaves in a tree model, the model would be

$$g\left(P_t; \theta, L\right) = \sum_{l=1}^{L} \theta_l \mathbf{1}_{\{P_t \in \mathit{leaf}_l\}}. \tag{34}$$

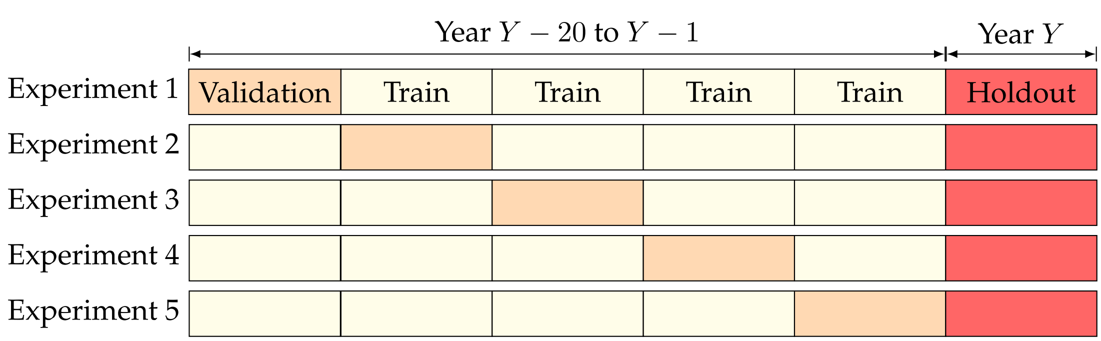
Random forest is an ensemble method that takes average of many decorrelated trees with bootstrapped observations and a random subset of features. Random forests attenuate overfitting in bootstrapped samples and make reliable out-of-sample predictions.

C.1.4 Cross-Validation

Many machine learning methods require tuning hyperparameters. We adopt a deterministic five-fold cross-validation scheme as illustrated in Figure C.1. To predict returns in year Y, we first split the past data up to the end of year $Y-1$ into five consecutive time intervals as five folds. Then, we train each model using four of the five folds and validate using the remaining one fold, resulting in five validation errors. Finally, we determine the best parameters according to the average of these five validation errors and refit the model using all five data folds.

Figure C.1: Deterministic Five-Fold Cross-Validation

This figure demonstrates the deterministic five-fold cross-validation scheme. At the beginning of each year, we re-estimate the models using data of the past 20 years. Specifically, the deterministic design divides the sample into five consecutive parts.



C.2 Other Predictive Models

C.2.1 Historical Average

We use the historical average of basis portfolio return over w periods as the prediction for next period return, which ignores any information in $\widetilde{Z}_{k,s,t}$ and x_t.

$$E_t(R_{t+1}) = \frac{1}{t} \sum_{\tau=t-w+1}^{\tau=t} R_\tau \tag{35}$$

C.2.2 Mean Combination

Combination method (Timmermann, 2006; Lin et al., 2018) is a practical solution to do prediction with a large number of predictors. The first step is to run univariate predictive regressions for each predictor j, and get multiple forecast values $\hat{R}_{t+1|t,j}$ for one return.

$$R_{t+1} = a_j + b_j P_{j,t} + \varepsilon_{j,t+1}. \tag{36}$$

$$\hat{R}_{t+1|t,j} = a_j + b_j P_{j,t}. \tag{37}$$

The second step is to combine the multiple forecasts with some weight, and get one single forecast for the return. We choose a naive but robust mean combination approach, which combines the multiple forecast values with equal weight.

$$\hat{R}^{MC}_{t+1|t} = \sum_{j=1}^{J} \frac{1}{J} \hat{R}_{t+1|t,j}. \tag{38}$$

D Predictor List

Table D.1: Predictor List

Acronym	Description	Details
		Macro Predictors
Bond market variable		
TERM	Term factor	Long-term government bond return (from Ibbotson Associates) minus the one-month Treasury bill rate
DEF	Default factor	Long-term corporate bond return minus long-term government bond return (from Ibbotson Associates)
CP5	Cochrane-Piazzesi forward factor	Codes of Monika Piazzesi, 5-year specification
ILL	Pastor-Stambaugh illiquidity	Download from Robert Stambaugh
TBL	3-month treasury bill rate	Download from Fed. St. Louis
CBMKT	Corporate bond market return	Value-weighted corporate bond market return, equal weight
MTS	Maturity spread	Return of long (greater than 10 years) maturity corporate bond returns minus return of short (2 to 5 years) maturity corporate bond returns, equal weight
RTS	Rating spread	Return of Junk bond minus return of AAA bond, equal weight
INFL	CPI index	Download from Fed. St. Louis
TMS	Term spread	Long-term yield on government bonds (from Ibbotson Associates) minus the one-month Treasury bill rate
DFY	Default yield spread	Yield of BAA- corporate bond minus yield of AAA corporate bonds
Equity market variable		
DP	Dividend-to-price	S&P500 index dividend-to-price
EP	Earnings-to-price	S&P500 index earnings-to-price
NI	Net equity issuance	S&P500 index net equity issuance
LEV	Leverage	S&P500 index leverage
SVAR	Stock variance	S&P500 index variance
MKTRF	Market factor	Download from Kenneth French
SMB	Size factor	Download from Kenneth French
HML	Value factor	Download from Kenneth French
MOM	Momentum factor	Download from Kenneth French
		Corporate Bond Characteristics
Fundamental		
CRT	Credit Rating	From FISD
TMT	Time-to-maturity	From FISD
AGE	Time-from-issuance	From FISD
SIZE	Amount outstanding	From FISD
CPN	Coupon rate	From FISD
Return-distribution		
STR	Short-term Reversal	Lag 1-month return
MOM6M	6-month momentum	Lag 2-month to lag 6-month cumulative return
MOM12M	12-month momentum	Lag 2-month to lag 12-month cumulative return
LTR2Y	2-year long-term reversal	Lag 13-month to lag 24-month cumulative return
LTR3Y	3-year long-term reversal	Lag 13-month to lag 36-month cumulative return
VAR	Variance	Variance of returns of the past 36 months
DSD	Downside risk	5% VaR of returns of the past 36 months
SKEW	Skewness	Skewness of returns of the past 36 months
KURT	Kurtosis	Kurtosis of returns of the past 36 months
Covariance on risk factors		
BETA_MKT	Multiple regression beta of a five-factor model	
BETA_SMB	Multiple regression beta of a five-factor model	
BETA_HML	Multiple regression beta of a five-factor model	
BETA_DEF	Multiple regression beta of a five-factor model	
BETA_TERM	Multiple regression beta of a five-factor model	
RVAR	Residual variance in the multiple regression of a five-factor model	

E Alternative Specifications of BCM Weights

Table E.1: LASSO Estimation: Weight (%) for Benchmark Combination Model

This table reports the in-sample weight (in percentage) for BCM estimated by LASSO. Specifically, we apply the standard LASSO package (`glmnet` in `R`) to run the penalized regression, constraining the upper and lower limits of coefficients to be 1 and 0. After that, we re-scale the weights to be sum-to-unity. The format follows Table 2.

	1976-2020	Expansion	Recession	1976-1980	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2020
Rating	24	18	35	8	22	15	0	0	18	45	20	23
Maturity	24	41	0	34	0	48	35	30	42	0	41	36
Size	0	0	0	0	0	0	0	28	0	0	0	0
Age	0	0	0	0	0	0	0	0	0	0	0	0
Coupon	0	0	0	0	0	0	0	0	0	0	0	1
S-term Rev	28	33	19	16	17	14	34	26	40	21	37	10
Mom 6M	0	0	0	0	5	3	10	1	0	0	0	0
Mom12M	8	4	14	0	15	3	20	0	0	7	0	0
L-term Rev 2Y	0	0	0	3	0	0	0	0	0	0	0	0
L-term Rev 3Y	0	0	0	0	0	0	0	14	0	0	0	0
Variance	16	4	32	33	40	0	0	0	0	17	0	29
Downside Risk	0	0	1	6	0	1	0	0	0	10	0	0
Skewness	0	0	0	0	0	0	0	0	0	0	0	0
Kurtosis	0	0	0	0	0	0	0	0	0	0	0	0
Beta_mktrf	0	0	0	0	0	0	0	0	0	0	2	0
Beta_smb	0	0	0	0	0	0	1	0	0	0	0	0
Beta_hml	0	0	0	0	0	0	0	0	0	0	0	0
Beta_term	0	0	0	0	0	0	0	0	0	0	0	0
Beta_def	0	0	0	0	0	0	0	0	0	0	0	0
Residual Variance	0	0	0	0	0	16	0	0	0	0	0	0
Bootstrap Positive Frequency			[0, 10%)		[10%, 50%)			[50%, 90%)			[90%, 100%]	

Table E.2: LASSO Estimation: Out-of-Sample Weight (%) for Benchmark Combination Model

This table reports the out-of-sample weight (in percentage) for BCM estimated by LASSO. The format follows Table 3.

	Rating	Maturity	Size	Age	Coupon	S-term Rev	Mom 6M	Mom12M	L-term Rev 2Y	L-term Rev 3Y	Variance	Downside Risk	Skewness	Kurtosis	Beta_mktrf	Beta_smb	Beta_hml	Beta_term	Beta_def	Residual Variance
1981	8	34	0	0	0	16	0	0	3	0	33	6	0	0	0	0	0	0	0	0
1982	3	26	0	0	0	20	11	0	1	0	38	1	0	0	0	0	0	0	0	0
1983	4	17	0	0	0	16	2	6	2	1	50	0	0	0	0	0	1	0	0	0
1984	5	12	0	0	0	17	3	7	1	1	53	0	0	0	0	0	1	0	0	0
1985	14	0	0	0	0	21	4	18	0	1	42	0	0	0	0	0	0	0	0	0
1986	22	0	0	0	0	17	6	15	0	0	40	0	0	0	0	0	0	0	0	0
1987	28	0	0	0	0	18	3	19	0	0	31	0	0	0	0	0	0	0	0	0
1988	33	0	0	0	0	20	17	18	0	0	13	0	0	0	0	0	0	0	0	0
1989	38	0	0	0	0	20	21	17	0	0	5	0	0	0	0	0	0	0	0	0
1990	37	40	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	10
1991	15	49	0	0	0	14	3	3	0	0	0	1	0	0	0	0	0	0	0	16
1992	18	53	0	0	0	7	1	6	0	0	0	0	0	0	0	2	0	0	0	14
1993	0	33	0	0	39	6	0	4	0	0	1	1	0	0	0	1	0	0	0	15
1994	0	41	0	0	38	7	0	3	0	0	0	0	0	0	0	0	0	0	0	11
1995	0	37	2	0	6	32	1	17	0	0	0	0	0	0	1	1	0	0	4	0
1996	0	35	0	0	0	34	9	20	0	0	0	0	0	0	0	1	0	0	0	0
1997	0	23	0	0	0	31	20	10	6	10	0	0	0	0	0	0	0	0	0	0
1998	0	27	0	0	0	28	11	14	0	12	0	0	0	0	0	8	0	0	0	0
1999	0	25	7	0	0	32	8	10	0	11	0	0	0	0	0	7	0	0	0	0
2000	0	27	16	0	0	28	8	4	0	12	0	0	0	0	0	5	0	0	0	0
2001	0	30	28	0	0	26	1	0	0	14	0	0	0	0	0	0	0	0	0	0
2002	0	32	41	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	2	23	36	0	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	8	37	17	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	15	41	4	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	18	42	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	18	45	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2008	20	50	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	50	31	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2010	44	1	0	0	0	21	0	7	0	0	18	9	0	0	0	0	0	0	0	0
2011	45	0	0	0	0	21	0	7	0	0	17	10	0	0	0	0	0	0	0	0
2012	45	0	0	0	0	24	0	7	0	0	13	10	0	0	0	0	0	0	0	0
2013	44	0	0	0	0	23	0	10	0	0	13	11	0	0	0	0	0	0	0	0
2014	21	0	0	0	0	29	0	14	0	0	10	27	0	0	0	0	0	0	0	0
2015	29	36	0	0	0	33	0	0	0	0	0	1	0	0	0	0	0	0	0	0
2016	20	41	0	0	0	37	0	0	0	0	0	0	0	0	2	0	0	0	0	0
2017	19	57	0	0	0	18	0	6	0	0	0	0	0	0	0	0	0	0	0	0
2018	20	60	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2019	16	62	0	0	0	20	0	0	0	0	2	0	0	0	0	0	0	0	0	0
2020	15	62	0	0	0	19	0	1	0	0	3	1	0	0	0	0	0	0	0	0
Bootstrap Positive Frequency						[0, 10%)				[10%, 50%)				[50%, 90%)				[90%, 100%]		

Table E.3: Stepwise Selection Estimation: Weight (%) for Benchmark Combination Model

This table reports the in-sample weight (in percentage) for BCM estimated by Stepwise Selection Regression. Specifically, we run forward stepwise regression with "BIC" selection criteria, and each regression has sum-to-unity constraint and non-negativity constraint. Format follows Table 2.

	1976-2020	Expansion	Recession		1976-1980	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2020
Rating	27	19	38		10	23	17	0	0	20	51	24	26
Maturity	26	44	0		35	0	54	39	34	47	0	48	39
Size	0	0	0		0	0	0	0	31	0	0	0	0
Age	0	0	0		0	0	0	0	0	0	0	0	0
Coupon	0	0	0		0	0	0	0	0	0	0	0	0
S-term Rev	30	36	20		17	18	16	37	29	44	23	43	11
Mom 6M	0	0	0		0	6	0	11	0	0	0	0	0
Mom12M	8	5	15		0	16	0	21	0	0	8	0	0
L-term Rev 2Y	0	0	0		0	0	0	0	0	0	0	0	0
L-term Rev 3Y	0	0	0		0	0	0	0	16	0	0	0	0
Variance	17	4	35		35	42	0	0	0	0	19	0	32
Downside Risk	0	0	0		7	0	0	0	0	0	12	0	0
Skewness	0	0	0		0	0	0	0	0	0	0	0	0
Kurtosis	0	0	0		0	0	0	0	0	0	0	0	0
Beta_mktrf	0	0	0		0	0	0	0	0	0	0	0	0
Beta_smb	0	0	0		0	0	0	0	0	0	0	0	0
Beta_hml	0	0	0		0	0	0	0	0	0	0	0	0
Beta_term	0	0	0		0	0	0	0	0	0	0	0	0
Beta_def	0	0	0		0	0	0	0	0	0	0	0	0
Residual Variance	0	0	0		0	0	18	0	0	0	0	0	0
Bootstrap Positive Frequency			[0, 10%)			[10%, 50%)			[50%, 90%)			[90%, 100%]	

Table E.4: Stepwise Selection Estimation: Out-of-Sample Weight (%) for Benchmark Combination Model

This table reports the out-of-sample weight (in percentage) for BCM estimated by Stepwise Selection Regression. The format follows Table 3.

	Rating	Maturity	Size	Age	Coupon	S-term Rev	Mom 6M	Mom12M	L-term Rev 2Y	L-term Rev 3Y	Variance	Downside Risk	Skewness	Kurtosis	Beta_mktrf	Beta_smb	Beta_hml	Beta_term	Beta_def	Residual Variance
1981	10	35	0	0	0	17	0	0	0	0	35	7	0	0	0	0	0	0	0	0
1982	3	27	0	0	0	21	12	0	0	0	40	0	0	0	0	0	0	0	0	0
1983	6	19	0	0	0	17	0	8	0	0	53	0	0	0	0	0	0	0	0	0
1984	7	13	0	0	0	18	0	9	0	0	56	0	0	0	0	0	0	0	0	0
1985	15	0	0	0	0	22	0	22	0	0	46	0	0	0	0	0	0	0	0	0
1986	23	0	0	0	0	18	6	16	0	0	42	0	0	0	0	0	0	0	0	0
1987	31	0	0	0	0	20	0	22	0	0	34	0	0	0	0	0	0	0	0	0
1988	37	0	0	0	0	22	18	19	0	0	14	0	0	0	0	0	0	0	0	0
1989	41	0	0	0	0	22	23	19	0	0	5	0	0	0	0	0	0	0	0	0
1990	40	43	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	11
1991	17	54	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	18
1992	22	58	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	16
1993	0	40	0	0	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23
1994	0	48	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17
1995	0	45	0	0	0	38	0	24	0	0	0	0	0	0	0	0	0	0	0	0
1996	0	39	0	0	0	37	11	21	0	0	0	0	0	0	0	0	0	0	0	0
1997	0	27	0	0	0	34	22	10	0	16	0	0	0	0	0	0	0	0	0	0
1998	0	30	0	0	0	31	13	15	0	13	0	0	0	0	0	8	0	0	0	0
1999	0	28	8	0	0	35	9	12	0	12	0	0	0	0	0	8	0	0	0	0
2000	0	30	18	0	0	31	11	0	0	14	0	0	0	0	0	7	0	0	0	0
2001	0	34	31	0	0	29	0	0	0	16	0	0	0	0	0	0	0	0	0	0
2002	0	35	46	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	0	26	41	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	9	41	19	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	19	47	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	20	47	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	20	50	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2008	22	56	0	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	56	36	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2010	50	0	0	0	0	24	0	8	0	0	20	11	0	0	0	0	0	0	0	0
2011	51	0	0	0	0	23	0	8	0	0	19	12	0	0	0	0	0	0	0	0
2012	51	0	0	0	0	28	0	8	0	0	15	12	0	0	0	0	0	0	0	0
2013	49	0	0	0	0	27	0	11	0	0	14	12	0	0	0	0	0	0	0	0
2014	24	0	0	0	0	33	0	15	0	0	11	30	0	0	0	0	0	0	0	0
2015	34	41	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2016	24	48	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2017	21	64	0	0	0	20	0	6	0	0	0	0	0	0	0	0	0	0	0	0
2018	23	67	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2019	19	70	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2020	17	72	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Bootstrap Positive Frequency	[0, 10%)	[10%, 50%)	[50%, 90%)	[90%, 100%]

Table E.5: Value-Weighted Portfolio Estimation: Weight (%) for Benchmark Combination Model

We estimate the BCM weight with sum-to-unity constraint and non-negativity constraint, and the sorted portfolios are weighted by bond size. Format follows Table 2.

	1976-2020	Expansion	Recession		1976-1980	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2020
Rating	29	24	35		1	13	6	0	0	28	43	32	19
Maturity	6	21	0		33	0	55	20	13	7	0	25	32
Size	35	42	24		0	0	4	70	82	46	32	19	19
Age	0	0	0		0	0	0	0	0	0	0	0	0
Coupon	0	0	0		0	0	0	0	0	0	0	0	4
S-term Rev	13	14	3		18	19	14	5	8	18	2	22	2
Mom 6M	0	0	0		0	5	4	0	0	0	0	0	0
Mom12M	2	0	11		0	17	3	0	0	0	3	1	0
L-term Rev 2Y	0	0	0		0	0	0	0	0	0	0	0	0
L-term Rev 3Y	0	0	0		0	0	0	0	0	0	0	0	0
Variance	15	0	25		39	46	0	0	0	0	8	2	24
Downside Risk	0	0	2		9	0	2	1	0	0	11	0	0
Skewness	0	0	0		0	0	0	0	0	0	0	0	0
Kurtosis	0	0	0		0	0	0	0	0	0	0	0	0
Beta_mktrf	0	0	0		0	0	0	0	0	0	0	0	0
Beta_smb	0	0	0		0	0	0	0	0	0	0	0	0
Beta_hml	0	0	0		0	0	0	9	0	0	0	0	0
Beta_term	0	0	0		0	0	0	0	0	0	0	0	0
Beta_def	0	0	0		0	0	0	0	0	0	0	0	0
Residual Variance	0	0	0		0	0	12	0	0	0	0	0	0
Bootstrap Positive Frequency			[0, 10%)			[10%, 50%)			[50%, 90%)			[90%, 100%]	

Table E.6: Value-Weighted Portfolio Estimation: Out-of-Sample Weight (%) for Benchmark Combination Model

This table reports the out-of-sample weight (in percentage) for BCM estimated with value-weighted portfolio returns. Format follows Table 3.

	Rating	Maturity	Size	Age	Coupon	S-term Rev	Mom 6M	Mom12M	L-term Rev 2Y	L-term Rev 3Y	Variance	Downside Risk	Skewness	Kurtosis	Beta_mktrf	Beta_smb	Beta_hml	Beta_term	Beta_def	Residual Variance
1981	1	33	0	0	0	18	0	0	0	0	39	9	0	0	0	0	0	0	0	0
1982	0	26	0	0	0	24	10	0	0	0	44	0	0	0	0	0	0	0	0	0
1983	0	18	0	0	0	18	3	5	0	0	58	0	0	0	0	0	0	0	0	0
1984	0	12	0	0	0	20	3	7	0	0	61	0	0	0	0	0	0	0	0	0
1985	4	0	0	0	0	24	4	20	0	0	48	0	0	0	0	0	0	0	0	0
1986	13	0	0	0	0	19	5	17	0	0	46	0	0	0	0	0	0	0	0	0
1987	23	0	0	0	0	18	0	21	0	0	37	0	0	0	0	0	0	0	0	0
1988	30	0	0	0	0	23	17	21	0	0	10	0	0	0	0	0	0	0	0	0
1989	37	0	0	0	0	22	23	18	0	0	0	0	0	0	0	0	0	0	0	0
1990	28	51	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	14
1991	6	55	4	0	0	14	4	3	0	0	0	2	0	0	0	0	0	0	0	12
1992	13	55	7	0	0	10	5	1	0	0	0	0	0	0	0	0	0	0	0	10
1993	0	34	0	0	26	14	0	7	0	0	4	0	0	0	0	0	0	0	0	14
1994	0	44	15	0	19	16	0	2	0	0	0	0	0	0	0	0	0	0	0	7
1995	0	23	64	0	2	11	0	1	0	0	2	0	0	0	0	0	0	0	0	0
1996	0	20	70	0	0	5	0	0	0	0	0	1	0	0	0	0	9	0	0	0
1997	0	15	70	0	0	5	1	4	8	0	0	0	0	0	0	0	0	0	0	0
1998	0	20	74	0	0	4	0	5	1	0	0	0	0	0	0	0	0	0	0	0
1999	0	16	79	0	0	6	0	2	0	0	0	0	0	0	0	0	0	0	0	0
2000	0	17	82	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2001	0	13	82	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2002	0	10	84	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	10	0	75	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	20	2	62	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	26	5	52	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	28	7	46	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	34	13	33	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2008	40	20	24	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	46	12	33	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2010	43	0	31	0	0	4	0	3	0	0	8	10	0	0	0	0	0	0	0	0
2011	43	0	32	0	0	2	0	3	0	0	8	11	0	0	0	0	0	0	0	0
2012	43	0	31	0	0	6	0	2	0	0	5	13	0	0	0	0	0	0	0	0
2013	42	0	30	0	0	3	0	4	0	0	6	15	0	0	0	0	0	0	0	0
2014	32	0	21	0	0	4	0	8	0	0	9	25	0	0	0	0	0	0	0	0
2015	32	15	29	0	0	15	0	3	0	0	2	3	0	0	0	0	0	0	0	0
2016	32	25	19	0	0	22	0	1	0	0	2	0	0	0	0	0	0	0	0	0
2017	32	40	16	0	0	2	0	7	0	3	0	0	0	0	0	0	0	0	0	0
2018	34	42	19	0	0	2	0	1	0	3	0	0	0	0	0	0	0	0	0	0
2019	24	46	24	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0
2020	28	49	19	0	0	0	0	0	0	1	4	0	0	0	0	0	0	0	0	0
Bootstrap Positive Frequency						[0, 10%)				[10%, 50%)					[50%, 90%)			[90%, 100%]		

F Factor Model Performance by Period

Table F.1: Fama-French Five-Factor Model Performance

Format follows Table 4. The factor model is MKT, SMB, HML, TERM, and DEF (Fama and French, 1993).

	INS		OOS	
Time Range	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
Panel A: Total R^2 %				
1976-2020	13.72	-18.31	-13.94	-45.18
Expansion	8.68	-19.46	-14.02	-48.87
Recession	22.90	-8.82	-13.78	-15.12
1976-1980	26.47	-46.44		
1981-1985	23.81	-15.05	2.68	-103.04
1986-1990	-7.04	-42.96	-73.46	-106.41
1991-1995	16.78	-25.77	13.97	-24.98
1996-2000	11.27	2.81	-17.80	-41.60
2001-2005	-11.93	-30.94	-5.48	-6.38
2006-2010	26.83	6.57	-24.09	-33.48
2011-2015	4.27	-2.43	-27.54	-34.42
2016-2020	21.50	-10.10	-8.03	-11.33
Panel B: Predictive R^2 %				
1976-2020	-0.41	-1.48	-1.30	-3.04
Expansion	-0.60	-1.73	-1.68	-3.47
Recession	-0.06	0.56	-0.59	0.50
1976-1980	-1.79	-3.52		
1981-1985	1.16	-0.70	1.11	-0.19
1986-1990	2.24	-3.43	-3.85	-20.56
1991-1995	-3.34	-6.47	1.07	4.00
1996-2000	-4.41	-3.92	-12.44	-12.49
2001-2005	-0.04	-0.88	0.88	1.04
2006-2010	0.30	0.01	-0.91	-1.48
2011-2015	2.65	2.88***	2.80	2.85***
2016-2020	1.89	2.91**	2.02	2.82*

Table F.2: Bai Bali Wen Four-Factor Model Performance

Format follows Table 4. The factor model is MKTbond, DRF, CRF, and LRF (Bai et al., 2019). The "46.71(NA)" ("-0.45(NA)") in row Recession of the last column means the average R^2 during recession period (March and April in 2020) is 46.71% (-0.45%), but we cannot calculate t-statistics for it as we have only two points (March and April 2020).

	INS		OOS	
Time Range	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
		Panel A: Total R^2 %		
1976-2020	38.75	20.70***	15.29	9.17***
Expansion	24.30	18.98***	11.16	8.61***
Recession	51.04	35.76***	45.63	46.71(NA)
2001-2005	24.14	19.46***		
2006-2010	40.80	18.52***	5.54	-1.40
2011-2015	22.39	14.68***	7.23	1.14
2016-2020	55.04	29.73***	35.81	20.98***
		Panel B: Predictive R^2 %		
1976-2020	-0.59	-1.82	4.05	1.36
Expansion	-0.38	-1.76	4.97	1.39
Recession	-0.95	-2.51	-2.67	-0.45(NA)
2001-2005	-0.13	-0.65		
2006-2010	-0.31	-3.85	7.80	6.48*
2011-2015	2.47	0.78	0.96	-2.40
2016-2020	2.00	-0.61	3.59	3.71

G Predicting Basis Portfolio Returns

This section presents the return predictability evidence for basis portfolios. We report the aggregate out-of-sample R^2 (Eq. 15) of five basis portfolios for each characteristic. Consistent with Lin et al. (2014) and Lin et al. (2018), we find that Mean Combination Forecast can predict the rating or maturity basis portfolio returns. Furthermore, we find that machine learning methods can substantially improve forecast performance.

In Table G.1, we extend the return predictability studies to all 20 groups of basis portfolio returns. We find high return predictability for all basis portfolios over their historical average. The traditional mean combination forecast method delivers robust predictability. Moreover, machine learning methods, including LASSO, PCA regression, and Random Forest, generate strong return predictability. This paper's results constitute another contribution: basis portfolio returns are predictable, primarily via machine learning methods. We put this section in the appendix because it is not the main contribution.

Table G.1: Predicting Corporate Bond Basis Portfolio Returns

This table reports the out-of-sample R^2_{OOS} (%) of return forecasts for basis bond portfolios. The prediction methods are listed for each column, and the out-of-sample prediction baseline is the historical average return of each basis portfolio. We aggregate the results for the five basis portfolios of each one of the 20 characteristics, see Eq. 15.

Characteristic	MeanComb	LASSO	PCA	Random Forest
Rating	3.25	9.48	12.46	9.17
Maturity	2.99	10.48	10.44	9.41
Size	3.28	10.31	9.54	10.39
Age	3.25	13.79	11.48	11.29
Coupon	3.15	11.03	10.49	10.34
Short-term Rev	2.99	12.92	9.94	11.07
Momentum 6M	2.75	10.89	11.36	9.41
Momentum 12M	2.68	12.35	10.86	9.42
Long-term Rev 2Y	3.95	15.64	13.62	11.72
Long-term Rev 3Y	3.43	11.44	10.79	9.92
Variance	2.69	9.97	10.44	9.29
Downside Risk	2.98	8.82	11.59	9.62
Skewness	2.92	9.29	6.95	10.05
Kurtosis	3.22	14.16	10.27	10.63
Beta_mkt	2.58	8.45	9.89	8.94
Beta_smb	3.20	12.21	10.37	9.61
Beta_hml	2.98	12.41	9.87	10.08
Beta_term	2.82	11.29	7.78	9.76
Beta_def	3.12	11.82	10.09	10.13
Residual Var.	2.75	8.38	11.29	9.46

H BCM Performance with Value-Weighted Basis Portfolio

Table H.1: Value-Weighted Basis Portfolio: Pricing Performance for Individual Corporate Bonds (In-Sample Result)

Format follows Table 4.

	All Bond		Investment Grade Bond		Non-Investment Grade Bond	
Time Range	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
Panel A: Total R^2 %						
1976-2020	36.59	35.83***	38.27	36.97***	28.32	23.36***
Expansion	34.67	35.70***	36.50	37.12***	24.24	21.81***
Recession	40.90	39.80***	42.80	38.98***	33.52	32.41***
1976-1980	84.63	65.13***	87.17	67.40***	40.06	16.03***
1981-1985	75.03	59.23***	77.04	61.37***	41.77	33.80***
1986-1990	56.48	44.25***	62.67	47.72***	30.38	22.61***
1991-1995	38.21	43.72***	40.75	42.72***	20.90	27.72***
1996-2000	29.14	23.47***	29.65	23.74***	23.72	18.62***
2001-2005	23.92	20.41***	25.02	20.98***	19.22	15.77***
2006-2010	26.34	20.53***	24.30	19.67***	32.30	18.95***
2011-2015	30.30	25.02***	30.58	24.76***	28.81	22.74***
2016-2020	50.25	32.22***	50.47	33.48***	49.34	17.74***
Panel B: Predictive R^2 %						
1976-2020	0.58	1.38**	0.46	1.12	1.18	2.30***
Expansion	0.69	1.42**	0.50	1.15**	1.81	2.23***
Recession	0.80	2.19	1.06	2.42	-0.23	1.65
1976-1980	0.11	-6.72	0.21	-7.02	-1.55	-8.52
1981-1985	1.35	-2.86	1.24	-3.23	3.08	-0.60
1986-1990	3.00	-2.88	2.94	-5.37	3.25	2.20
1991-1995	0.58	5.76**	0.34	5.88**	2.25	5.74***
1996-2000	5.40	0.54	5.44	0.44	4.92	0.21
2001-2005	3.04	3.00**	2.87	2.89**	3.80	3.10**
2006-2010	0.48	-0.72	0.38	-0.95	0.77	0.24
2011-2015	6.63	6.55***	6.35	6.14***	8.17	7.18***
2016-2020	4.41	4.04	4.74	3.74	3.03	5.94

Table H.2: Value-Weighted Basis Portfolio: Pricing Performance for Individual Corporate Bonds (Out-of-Sample Result)

Format follows Table 5.

	All Bond		Investment Grade Bond		Non-Investment Grade Bond	
Time Range	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
Panel A: Total R^2 %						
1976-2020	32.77	33.02***	33.94	34.00***	27.46	22.06***
Expansion	31.33	32.58***	32.75	33.90***	23.66	21.19***
Recession	35.53	36.58***	36.40	34.83***	32.50	29.07***
1981-1985	74.34	58.26***	76.49	60.67***	38.69	29.92***
1986-1990	54.67	43.33***	60.21	46.21***	31.32	24.72***
1991-1995	36.25	42.79***	38.62	44.81***	20.00	26.04***
1996-2000	28.87	23.11***	29.42	23.42***	22.97	17.77***
2001-2005	23.16	20.22***	24.64	21.06***	16.82	14.38***
2006-2010	25.58	20.74***	23.97	20.03***	30.29	18.59***
2011-2015	28.76	23.98***	28.28	23.17***	31.37	24.46***
2016-2020	49.48	32.07***	49.45	33.04***	49.62	20.63***
Panel B: Predictive R^2 %						
1976-2020	0.06	0.79	-0.08	0.61	0.73	1.89***
Expansion	0.46	1.00*	0.25	0.76	1.65	2.23***
Recession	-0.45	-0.90	-0.51	-0.58	-0.27	-0.81
1981-1985	-2.54	-2.57	-2.62	-2.69	-1.24	-1.22
1986-1990	0.34	-2.84	0.09	-3.60	1.92	1.24
1991-1995	0.09	5.00***	-0.58	4.99**	4.63	5.98***
1996-2000	-1.99	-1.53	-2.04	-1.54	-1.52	-1.24
2001-2005	0.76	0.90**	0.73	0.88**	0.87	0.94**
2006-2010	0.33	0.53	0.29	0.43	0.43	0.85
2011-2015	2.84	3.31***	2.58	3.00***	4.24	4.33***
2016-2020	2.32	3.63***	2.49	3.53***	1.61	4.33***

Table H.3: Value-Weighted Basis Portfolio: Predicting Individual Bond Returns with BCM Forecast

Format follows Table 8.

	All Bond		IG Bond		NIG Bond	
Model	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$	R^2	FM-$\overline{R^2}$
Panel A: Prediction Period 1996 Jan - 2020 Sep						
BCM-AVG	0.25	0.12	0.25	0.21	0.26	-0.20
BCM-MEANC	0.92	1.08***	0.91	1.16***	0.92	0.71**
BCM-LASSO	3.09	1.82**	2.78	1.80**	4.35	1.49
BCM-PCA	3.36	1.85*	2.83	1.65	5.51	1.84
BCM-RF	3.19	2.95***	3.37	3.04***	2.43	1.96**
FF5	-0.69	-1.68	-0.85	-1.75	-0.02	-0.88
Panel B: Expansion						
BCM-AVG	0.22	0.13	0.21	0.22	0.27	-0.20
BCM-MEANC	1.16	1.20***	1.22	1.30***	0.87	0.77**
BCM-LASSO	3.30	2.00**	3.25	2.02**	3.58	1.48
BCM-PCA	4.46	2.21**	4.27	2.08**	5.40	1.97
BCM-RF	4.79	3.32***	5.06	3.43***	3.42	2.17**
FF5	-1.20	-1.83	-1.41	-1.94	-0.12	-0.87
Panel C: Recession						
BCM-AVG	0.32	0.08	0.35	0.14	0.25	-0.20
BCM-MEANC	0.48	-0.07	0.31	-0.14	0.97	0.17
BCM-LASSO	2.71	0.06	1.84	-0.37	5.23	1.56
BCM-PCA	1.39	-1.64	-0.08	-2.48	5.63	0.63
BCM-RF	0.31	-0.59	-0.03	-0.72	1.30	-0.08
FF5	0.22	-0.21	0.27	0.03	0.10	-1.01
Panel D: Prediction Period 2009 Jul - 2020 Sep (for BBW4 data)						
BCM-AVG	1.36	0.66	1.49	0.90*	0.89	-0.84
BCM-MEANC	1.70	1.45***	1.76	1.65***	1.43	0.23
BCM-LASSO	4.42	1.14	4.23	1.29	5.15	-0.14
BCM-PCA	4.35	0.85	3.43	0.60	7.94	1.07
BCM-RF	4.15	2.54***	4.26	2.72***	3.71	0.94
FF5	0.51	-1.35	0.27	-1.47	1.46	-0.99
BBW4	3.36	1.19	2.89	1.33	5.23	-0.89

Table H.4: Value-Weighted Basis Portfolio: Forecast-Implied Long-Short Strategy Performance

Format follows Table 9.

	All Bond			IG Bond			NIG Bond		
Model	Avg.Ret	α	SR	Avg.Ret.	α	SR	Avg.Ret.	α	SR
Panel A: Prediction Period 1996 Jan - 2020 Sep									
BCM-AVG	0.50	0.39***	1.08	0.51	0.44***	1.28	0.41	0.37***	0.83
BCM-MEANC	0.50	0.42***	1.21	0.49	0.45***	1.34	0.36	0.33***	0.73
BCM-LASSO	0.37	0.31***	1.17	0.38	0.35***	1.38	0.31	0.30***	0.72
BCM-PCA	0.46	0.43***	1.33	0.40	0.38***	1.25	0.19	0.17***	0.42
BCM-RF	0.48	0.42***	1.29	0.51	0.48***	1.62	0.38	0.35***	0.85
Panel B: Expansion									
BCM-AVG	0.55	0.48***	1.62	0.53	0.49***	1.64	0.40	0.37***	1.04
BCM-MEANC	0.53	0.46***	1.67	0.50	0.46***	1.65	0.39	0.36***	0.98
BCM-LASSO	0.40	0.37***	1.66	0.40	0.39***	1.70	0.27	0.27***	0.76
BCM-PCA	0.46	0.40***	1.62	0.43	0.40***	1.61	0.30	0.26***	0.80
BCM-RF	0.55	0.53***	2.26	0.54	0.54***	2.28	0.38	0.37***	1.09
Panel C: Recession									
BCM-AVG	0.05	0.40	0.05	0.36	0.48	0.42	0.41	0.67	0.39
BCM-MEANC	0.23	0.64	0.24	0.44	0.67	0.59	0.11	0.46	0.11
BCM-LASSO	0.03	0.46	0.04	0.21	0.53	0.40	0.78	0.91	0.84
BCM-PCA	0.54	0.77	0.73	0.19	0.41	0.29	-0.83	-0.59	-0.93
BCM-RF	-0.17	0.57	-0.18	0.22	0.79***	0.30	0.41	0.90	0.41
Panel D: Prediction Period 2009 Jul - 2020 Sep (for BBW4 data)									
BCM-AVG	0.75	0.22***	1.72	0.72	0.22***	1.85	0.57	0.19**	1.50
BCM-MEANC	0.73	0.27***	1.82	0.67	0.24***	1.89	0.53	0.16	1.27
BCM-LASSO	0.44	0.19**	1.46	0.45	0.24***	1.71	0.20	0.12	0.68
BCM-PCA	0.65	0.32***	2.07	0.59	0.30***	2.02	0.34	0.05	0.92
BCM-RF	0.56	0.22**	1.54	0.55	0.25***	1.75	0.31	0.04	0.88