

Timing the corporate bond market

Zhenyu Lu*

Yi Cao[†]

Wenxuan Hou[‡]

Yiyan Qian[§]

This version: January, 2026

Abstract

This paper explores a data-driven approach to timing the corporate bond market using real-time macro-financial information. We implement a forecast combination method, which is conceptually linked to simple ensemble learning in machine learning, to predict excess bond returns and dynamically adjust market exposure. The resulting managed portfolio delivers significant improvements in risk-adjusted returns, Sharpe ratios, and investor utility, outperforming leading factor models both in- and out-of-sample. The strategy is particularly effective during periods of macroeconomic instability, demonstrating its adaptive power. Our findings contribute to the growing literature on AI-assisted investment strategies by showing how transparent, real-time prediction frameworks can enhance portfolio decisions in fixed-income markets without relying on black-box algorithms.

JEL classification: G12; G14; G17.

Keywords: Market timing; Time-series predictability; Corporate bond market; Portfolio choice; Managed portfolio.

*Department of Financial and Actuarial Mathematics, School of Mathematics and Physics, Xi'an Jiaotong-Liverpool University. Email: zhenyu.lu@xjtlu.edu.cn.

[†]Department of Financial and Actuarial Mathematics, School of Mathematics and Physics, Xi'an Jiaotong-Liverpool University. Email: yi.cao@xjtlu.edu.cn.

[‡]Corresponding author. University of Edinburgh Business School, University of Edinburgh. Email: wenxuan.hou@ed.ac.uk.

[§]Nottingham University Business School China, University of Nottingham Ningbo China; Nottingham University Business School, University of Nottingham. Email: yiyan.qian@nottingham.edu.cn.

1 Introduction

A fundamental question in modern finance literature is to understand why assets earn vastly different average returns in the cross section. In equity markets, the capital asset pricing model (CAPM) of [Sharpe \(1964\)](#), [Lintner \(1965\)](#), and [Black \(1972\)](#) with the value-weighted stock market factor is the cornerstone of the literature on understanding the determinants of the pricing kernel for stocks. An important implication of this model is that the market portfolio of invested wealth is mean-variance efficient, and thus is sufficient to summarize the entire investment opportunity set. Nevertheless, this assumption has been challenged by many studies. To surpass the market portfolio, the growing literature proposes strategies for managing investment portfolios either in the cross-sectional dimension, i.e., anomaly factor portfolios (see [Fama & French, 2015](#); [Hou et al., 2020](#), for example), or in the time-series dimension ([Farmer et al., 2023](#); [Hollstein & Prokopczuk, 2023](#); [Jiang et al., 2024](#); [Moreira & Muir, 2017](#); [Rapach et al., 2016](#), among others).

Managed strategy, on the other hand, is relatively underexplored for the corporate bond market. [Dickerson, Mueller, & Robotti \(2023\)](#) document that the market factor significantly predicts the cross-sectional variations in excess returns of corporate bonds.¹ From an investment perspective, they show that several newly proposed bond factors fail to outperform the value-weighted bond market factor. In other words, incorporating these factors into an investor's portfolio yields marginal improvements beyond what is achieved by simply holding the bond market portfolio. Therefore, the corporate bond market portfolio alone is important and has nontrivial pricing ability for corporate bonds ([van Binsbergen et al., 2023](#); [Dickerson, Mueller, & Robotti, 2023](#)). Meanwhile, the performance of the largest possible bond market portfolio is also attractive compared to sophisticated machine learning-based strategies ([Dickerson et al., 2024](#)) and after controlling for the transaction cost ([Ivashchenko & Kosowski, 2024](#)). Given the pivotal role played by the bond market portfolio, we focus our attention on enhancing such portfolio through a time-series managed strategy, i.e., timing the corporate bond market.²

As an asset allocation strategy, market timing is designed to dynamically change a portfolio's exposure to the aggregate market based on the prevailing market conditions inferred from con-

¹ Indeed, the market factor (portfolio) is commonly adopted in linear factor models to explain cross-sectional variations in returns of other asset classes, such as the average factor of [Bakshi et al. \(2019\)](#) in commodity futures markets, the dollar factor of [Lustig et al. \(2011\)](#) for currency markets, the market factor of [Liu et al. \(2022\)](#) in the cryptocurrency market, and the level factor of [Karakaya \(2014\)](#) for equity option markets.

² Recent literature has proposed several cross-sectionally managed investment strategies for corporate bond markets, including [Bali et al. \(2021\)](#), [Cao et al. \(2023\)](#), [Chen & Choi \(2024\)](#), [Chung et al. \(2019\)](#), [Elkamhi et al. \(2024\)](#), [Kelly et al. \(2023\)](#), among others. In this paper, we focus on the time-series managed portfolios only.

conditioning information, i.e., to invest more in good times and vice versa. The existing literature in equity markets shows that the aggregate market returns are predictable over time (see [Campbell, 1987](#); [Fama & French, 1988](#); [Lettau & Ludvigson, 2001](#); [Neely et al., 2014](#); [Rapach et al., 2010](#), for example), thereby offering investors the opportunity to engage in market timing. To proxy the conditioning information set, a common choice is the predictor variable, such as return predictors studied by [Welch & Goyal \(2008\)](#) that are widely used to forecast time variations in aggregate market returns. Building on this idea, recent work by [Hollstein & Prokopczuk \(2023\)](#) shows that managing the stock market portfolio with information from market excess return forecasts enhances the investment opportunity set of an investor who trades in static factor investing.³ More importantly, in the corporate bond market, existing studies also demonstrate the strong predictability of corporate bond returns (see [Keim & Stambaugh, 1986](#); [Fama & French, 1989](#); [Hong et al., 2012](#); [Greenwood & Hanson, 2013](#); [Lin et al., 2014, 2018](#); [He et al., 2022](#); [Feng et al., 2025](#); [Kelly et al., 2023](#), for example). It is therefore natural to relate such predictability to time-series management of bond market portfolio.

Our paper extends the idea of managing the market portfolio via time-series predictability to corporate bond markets. Following [Hollstein & Prokopczuk \(2023\)](#), we construct the managed bond market portfolio with conditioning information and evaluate its performance relative to cross-sectional asset pricing models as well as in an out-of-sample setting. By exploiting the time-series managed portfolio, this paper aims to advance our understanding of the conditional asset pricing in corporate bond markets, which has great implications for both practitioners and researchers. For example, managing the bond market portfolio could lead to sizable investment gains for investors and firms with a commercial interest. Besides, in the subsequent analysis, we show that the performance of managed portfolios is not spanned by well-known bond pricing factors, thus posing a new challenge for cross-sectional pricing models in corporate bond markets. More strikingly, our approach offers a transparent, ensemble-based alternative to black-box machine learning, and demonstrates how real-time data-driven signals can support adaptive investment strategies.

In the empirical exercises, we first show that excess returns of the corporate bond market portfolio are highly predictable using 15 well-known macroeconomic and financial predictor

³ Another direction to enhance portfolios in the time-series dimension is to manage their volatility. For instance, [Moreira & Muir \(2017\)](#) challenge the conventional risk-return trade-off and demonstrate that an investor can benefit from volatility timing by decreasing her exposure to risk factors when their volatility is elevated. [Barroso & Santa-Clara \(2015\)](#) and [Daniel & Moskowitz \(2016\)](#) also extend volatility-timing strategies to momentum portfolios. However, the performance of such managed portfolios is challenged by [Cederburg et al. \(2020\)](#) and [Barroso & Detzel \(2021\)](#) in terms of the investability.

variables. Results of univariate predictive regressions indicate that two-thirds of predictors have strong in-sample predictive ability for the bond market excess returns. However, similar to the findings in equity markets, only 4 individual predictors deliver consistent out-of-sample forecasting gains relative to the benchmark model based on the historical average forecast. One possible reason for the vanished out-of-sample performance is the model uncertainty or structural instability embedded in a single model (Rapach et al., 2010). Given the structural instability risk in an unstable environment (e.g., institutional changes and policy shocks), individual variables may provide accurate signals in certain periods but uninformative even false signals during others. Therefore, a single predictive model is less likely to accurately approximate the highly uncertain and complex data-generating process for expected corporate bond market returns.

To establish the out-of-sample predictability, we follow Rapach et al. (2010) and apply the forecast combination method to aggregate the out-of-sample bond market excess return forecasts derived from the information in individual predictors. Over the out-of-sample period from February 1991 to December 2022, we find that the forecast combination significantly improves the degree of predictive accuracy in statistical criteria. From an asset allocation perspective, such a combination approach also delivers considerable economic gains as measured by the certainty equivalent returns (CER) of 1.27% per year. These results underscore the benefits of forecast combination to enhance the predictability of corporate bond market portfolios.

Building on the evidence of time-series predictability, we implement a market timing strategy in the spirit of Hollstein & Prokopczuk (2023). Specifically, we dynamically alter the exposure to the bond market portfolio based on the return combination forecasts. The combination forecast-managed corporate bond market portfolio generates an annualized average excess return of 4.93% with a t -statistic of 2.48. This indicates that macroeconomic and financial variables contain useful information about the future market states for timing, thereby leading to a profitable managed portfolio. Next, we investigate whether the returns of managed market portfolios are spanned by existing corporate bond pricing factors. That is, to what extent timing the bond market can enhance the investment opportunity set of an investor who trades static pricing factors. By regressing managed portfolio returns on a set of factor models, we find that the combination forecast-managed bond market portfolio generates positive risk-adjusted returns ranging from 2.94% to 6.37%, which are all statistically significant at the 5% level. Meanwhile, our main findings are robust after controlling for the impact of transaction costs, using combination forecasts with time-varying weights, and imposing leverage constraints.

Moreover, we analyze the enhancement of existing factor models after incorporating the managed market portfolio. Following the approach of [Cederburg et al. \(2020\)](#), we compare the performance of optimal combination portfolios constructed using the factor model space either with or without the managed market portfolio. As the real-time implementation is noteworthy, we calculate the optimal investment weights in the combination portfolio based on information available to investors when they are required to construct trading strategies. Our results indicate significant improvements from augmenting factor models with the managed portfolio. In particular, the optimal combination strategies with managed market portfolio outperform original factor models by producing significantly increased out-of-sample Sharpe ratios (up to 0.35% per year) and economically large utility gains (up to 5.28% per year). Overall, our findings highlight the economic impact of adding time-series managed portfolio to the investment opportunity set.

What is the potential mechanism behind the superior performance of managed market portfolios? The time-varying macroeconomic risk channel suggests that risk premiums are compensations for investors who bear recession-related risks. Previous studies have shown that changes in economic fundamentals are the driving forces behind the time variations in expected bond returns ([Fama & French, 1989](#); [Lin et al., 2018](#); [Bianchi et al., 2021](#)). Motivated by this, we illustrate that the expected corporate bond market returns have a strong countercyclical pattern, and can reflect time-varying fundamental risks. This evidence confirms the strong link between expected bond market returns and macroeconomic risk, which is the key driver of bond return predictability. In addition, predictors of [Welch & Goyal \(2008\)](#) used in our analysis are often treated as state variables in characterizing the investment opportunity set and can predict economic activities in the long term ([Boons, 2016](#); [Maio & Santa-Clara, 2017](#); [Petkova, 2006](#)). This offers insight into why these predictors have predictability for bond market returns.

Building upon these analyses, we investigate an important implication of the market timing to better understand its economic source. In particular, we perform a two-regime analysis to evaluate the performance of managed portfolios under different economic conditions. Our results show that the managed portfolio achieves better performance when economic conditions are rapidly changing. For example, conditional on large absolute changes in industrial production, the managed portfolio delivers an annualized average return of 7.16% (t -statistic = 2.01) and statistically significant alphas ranging from 4.46% to 8.21%. In contrast, the average return of the portfolio is only 2.52% per year when conditional on small absolute changes in industrial production, and nearly all risk-adjusted returns are statistically insignificant. We obtain quali-

tatively similar results when using different proxies to represent changes in economic and market states. Based on these, we conclude that the superior performance of the managed portfolio is attributed to the ability of predictor variables to capture more rapidly changing economic and market states, i.e., during periods when the timing strategy is more relevant.

Lastly, we perform additional robustness checks in the following ways. First, we confirm that our baseline results remain valid when adopting three alternative proxies for the corporate bond market portfolio. Second, we split the full sample into crisis and normal periods and show that the superior performance of the corporate bond market timing strategy is not driven by extreme weights and returns concentrated in crisis times. Finally, we consider different return forecast combination methods and estimation schemes and verify that our results are not sensitive to specific research designs.

Related Literature – Our paper is related to the literature on the times-series predictability of returns for corporate bonds. Despite extensive research on stock return predictability (see [Ang & Bekaert, 2007](#); [Atanasov et al., 2020](#); [Bali, 2008](#); [Campbell & Thompson, 2008](#); [Cochrane, 2008](#); [Huang et al., 2015](#); [Rapach et al., 2010](#); [Rapach & Zhou, 2013](#); [Welch & Goyal, 2008](#), among others), there are only a few studies on the predictability of corporate bond returns. Early work by [Keim & Stambaugh \(1986\)](#) analyzes the common variation in expected returns on bonds and provides strong evidence that they are time-varying. [Fama & French \(1989\)](#) document that corporate bond returns are predictable by forecasting variables, such as the dividend yield and the default spread, both in- and out-of-sample. More recently, [Hong et al. \(2012\)](#) investigate the predictability of corporate bond market returns and find a strong nonlinear structure in the serial dependence for bond returns. [Greenwood & Hanson \(2013\)](#) find that the credit quality of corporate debt issuers can predict corporate bond returns. [Lin et al. \(2014\)](#) introduce additional forecasting variables and employ the combination forecast method for predicting the credit spread component of corporate bond returns. [Lin et al. \(2018\)](#) propose an iterated combination approach with a large set of predictors for predicting returns of bonds with different ratings and maturities. Moreover, [Bali et al. \(2022\)](#), [Feng et al. \(2025\)](#), [He et al. \(2022\)](#), [Kelly et al. \(2023\)](#) apply machine learning methods to model and predict corporate bond returns. Our paper aligns with this prevailing trend by investigating the time-series predictability of corporate bond market portfolios, but with a unique focus on the implication of predictability for investors’ portfolio management strategies.

Our work also builds on the literature on efficient timing strategy with conditioning informa-

tion. Earlier representative contributions include [Fleming et al. \(2001\)](#) and [Fleming et al. \(2003\)](#), which assess the economic value of volatility timing, and [Marquering & Verbeek \(2004\)](#), which evaluates the performance of trading strategies based on timing in returns and volatility. Recent works by [Barroso & Santa-Clara \(2015\)](#), [Cederburg et al. \(2020\)](#), [Daniel & Moskowitz \(2016\)](#), [DeMiguel et al. \(2024\)](#), and [Moreira & Muir \(2017\)](#) investigate the timing ability of volatility in various asset pricing factors. [Arnott et al. \(2023\)](#), [Ehsani & Linnainmaa \(2022\)](#), and [Gupta & Kelly \(2019\)](#) study the performance and implication of factor momentum strategies. [Haddad et al. \(2020\)](#) show that risk factors are robustly predictable and the optimal factor timing portfolio affects inference about the stochastic discount factor. To engage in market timing, [Jiang et al. \(2024\)](#) use economic narratives and machine learning methods to manage the equity market portfolios and [Maurer et al. \(2023\)](#) analyze the importance of market timing in foreign exchange markets utilizing information about the conditional Sharpe ratio. Contrary to these studies but aligning with [Haddad et al. \(2020\)](#), our research employs the conditioning information contained in a set of macroeconomic and financial variables to achieve efficient market timing. Early works have highlighted the importance of conditioning information in portfolio optimization: [Ferson & Siegel \(2001\)](#), [Ferson & Siegel \(2009\)](#), [Ferson et al. \(2019\)](#), and [Peñaranda \(2016\)](#). This motivates our choice to use lagged conditioning variables to infer the time-varying optimal weights for market portfolio optimization in real time. Our work is mostly related to the recent paper by [Hollstein & Prokopczuk \(2023\)](#), which manage the equity market portfolio utilizing time-series predictors. We differ from their work by focusing on the quickly developing but underexplored corporate bond markets and further investigating the economic mechanism underlying the performance of market timing. Noticeably, our paper is the first to analyze the market timing strategy with conditioning variables and quantify its economic benefits for real-time investors using corporate bond market data.

Finally, our study contributes to the rapidly growing literature on factor investing in the corporate bond market (see [Bali et al., 2022, 2024](#); [van Binsbergen et al., 2023](#); [Dick-Nielsen et al., 2023](#); [Dickerson, Robotti, & Rossetti, 2023](#); [Dickerson & Nozawa, 2024](#); [Kelly et al., 2023](#); [Nozawa et al., 2024](#), among others). Recent studies (e.g., [Dick-Nielsen et al., 2023](#); [Dickerson, Mueller, & Robotti, 2023](#)) raise concerns about several factors identified in the corporate bond markets. [van Binsbergen et al. \(2023\)](#) and [Dickerson, Mueller, & Robotti \(2023\)](#) show that several proposed bond risk factors can be spanned by the stock and bond market portfolios. [Dickerson et al. \(2024\)](#) find that the sophisticated machine learning-based trading strategies generate unattractive bond

CAPM alphas after accounting for transaction costs. Thus, the realistic outperformance of active bond trading strategies relative to the bond market factor is questionable. Similarly, by applying the principle of market microstructure invariance, [Ivashchenko & Kosowski \(2024\)](#) highlight that the investment performance of the largest possible bond market portfolios is robust to transaction costs. Motivated by these, we center our attention on the corporate bond market portfolio, which has nontrivial explanatory power for corporate bonds. By leveraging the time-series predictability related to factor investing, we contribute to the literature by offering an enhancement approach for the bond CAPM, and show that managed bond market portfolios add economic value for investors in cross-sectional factor strategies.

The rest of this paper is organized as follows. Section 2 describes the data and descriptive statistics. In Sections 3 and 4, we analyze the predictability of corporate bond market returns and present the main results for the market timing strategy based on the time-series predictability, respectively. Section 5 discusses the possible economic rationale for the performance of bond market timing. Section 6 provides robustness checks. Finally, Section 7 concludes.

2 Data

2.1 Predictors

In order to capture changes in macroeconomic and financial conditions and describe the conditioning information set of investors, we consider a set of predictors studied by [Welch & Goyal \(2008\)](#). These economic predictors are widely used in the equity and bond return predictability literature (see [Bali, 2008](#); [Boudoukh et al., 2007](#); [Campbell, 1987](#); [Campbell & Shiller, 1988](#); [Cochrane, 1991](#); [Fama & French, 1988, 1989](#); [Lettau & Ludvigson, 2001](#); [Lin et al., 2018](#); [Rapach & Zhou, 2013](#), among others). There are 15 macroeconomic and financial predictors in total, including log dividend-price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend-payout ratio (DE), stock return variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), Treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), inflation (INFL), and investment-to-capital ratio (IK). Detailed descriptions of these predictors are reported in [Appendix A](#). We collect the data on [Welch & Goyal \(2008\)](#) predictors from Amit Goyal’s website.⁴ For macroeconomic variables, we use the vintage data available for real-time

⁴ See <https://sites.google.com/view/agoyal145>. We thank Amit Goyal for making the data available.

investors at each point in time from the Archival Federal Reserve Bank of St. Louis FRED (ALFRED) database. The main sample period starts from January 1986 to December 2022.

We present summary statistics of the predictors in Panel A of Table 1. As indicated by the autocorrelation coefficients, many predictor variables (e.g., DP, DY, EP, DE, BM, NTIS, TBL, LTY, TMS, DFY, and IK) are highly persistent, suggesting a potential clustering effect in return forecasts made by these predictors. On the other hand, autocorrelations of other variables such as SVAR, LTR, and DFR are low. In addition, part of the variables (e.g., DE, SVAR, DFY) have high skewness and thus may create asymmetric weights in the managed bond market portfolio. DE, SVAR, DFY, DFR, and INFL have relatively high kurtosis exceeding 10, suggesting that they might imply extreme weights in the managed market portfolio when used alone.

2.2 Factor strategies

The corporate bond market portfolio (MKTB) is constructed by using corporate bond returns in excess of the one-month risk-free rate of return (Dickerson, Mueller, & Robotti, 2023). Dickerson, Julliard, & Mueller (2023) argue that the Intercontinental Exchange (ICE) corporate bond data is more suitable than the Trade Reporting and Compliance (TRACE) transaction-based data for academic research in terms of the data quality and sampling methods. Kelly et al. (2023) also note that the ICE data serves as the *gold standard* for empirical studies on corporate bond markets and should be the main data source for the corporate bond research.⁵ Therefore, following Dickerson, Julliard, & Mueller (2023), our paper adopts the corporate bond factors constructed using the ICE data set.⁶ For the empirical analysis, we consider 9 non-market corporate bond factor strategies, including the bond carry factor (CRY), the bond default risk factor (DEF), the bond duration factor (DUR), the bond long-term reversal factor (LTR), the bond momentum factor (MOMB), the bond earnings announcement drift factor (PEADB), the bond short-term reversal factor (STR), the bond term structure risk factor (TERM), and the bond value factor (VAL). For the corporate bond market portfolio and other tradable factors,

⁵ See Andreani et al. (2024) and Kelly & Pruitt (2022) for detailed comparison between the ICE and TRACE data.

⁶ To construct the corporate bond data set for empirical analysis, Dickerson, Julliard, & Mueller (2023) first rely on the constituents of the corporate bond data set from the Bank of America Merrill Lynch High Yield and Investment Grade indices obtained from the Intercontinental Exchange (ICE). This part of the sample covers the period from January 1997 to September 2021. In addition, for the remained sample period from January 1986 to December 1996, they utilize the Lehman Brothers Fixed Income Database (LHM). Then they merge it with the Mergent Fixed Income Securities Database (FISD) to obtain other required bond characteristics. See Dickerson, Julliard, & Mueller (2023) for detailed descriptions.

we collect data from the Open Source Bond Asset Pricing.⁷ As summarized in Panel B of Table 1, the corporate bond market portfolio has an economically large return of 0.32% per month, which is statistically significant at the 1% level. This points to an attractive investment by simply holding the market strategy. Among other bond risk factors, CRY, DUR, LTR, PEADB, TERM, and VAL are able to generate significant average returns.

Given the link between corporate bond and equity markets, we further consider 8 equity risk factors, including the equity market factor (MKTS), the size factor (SMB), the equity value factor (HML), the equity momentum factor (MOMS), the intermediary capital risk factor (HKM), the liquidity factor (LIQ), the profitability factor (RMW), and the investment factor (CMA). We collect the MKTS, SMB, HML, MOMS, RMW, and CMA from Kenneth R. French’s data library. Data on HKM is retrieved from Zhiguo He’s website. Finally, LIQ is obtained from Lubos Pastor’s website.⁸ In Appendix B, we provide detailed descriptions of all risk factors. Summary statistics for equity risk factors are provided in Panel C of Table 1.

3 Corporate bond market predictability

3.1 Methodology

We use a standard predictive regression model for forecasting the corporate bond market portfolio, which can be expressed as follows:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1}, \quad (1)$$

where r_{t+1} is the excess return of the corporate bond market portfolio at time $t + 1$, $x_{i,t}$ is the predictor i at time t whose predictive power is of interest, and ε_{t+1} is an error term with zero mean and unit variance. For the ease of economic interpretation, we standardize each predictor variable so that the β_i can be interpreted as the effect of a one standard deviation increase in predictor i on the next-month corporate bond market excess returns. We calculate the in-sample R^2 , the Newey & West (1986) (NW) t -statistics and the Hodrick (1992) (Hodrick) t -statistics with their bootstrapped p values for slope estimates β .

To generate out-of-sample forecasts of the corporate bond market portfolio for each predictor,

⁷ See <https://openbondassetpricing.com/>. We acknowledge Alex Dickerson, Philippe Mueller, Cesare Robotti, and Christian Julliard for making this data public.

⁸ The Kenneth R. French’s data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The Zhiguo He’s website: <https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/>. The Lubos Pastor’s website: <https://faculty.chicagobooth.edu/lubos-pastor/data>.

we use a recursive estimation window with an initial length of 60 monthly observations. We first split the full sample into in-sample and out-of-sample periods and then obtain the corporate bond market excess return forecasts with each predictor as follows:

$$\hat{r}_{i,t+1|t} = \hat{\alpha}_i + \hat{\beta}_i x_{i,t}, \quad (2)$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the estimated intercept and slope coefficients, respectively, from the predictive regression (1). Specifically, at time t , we use the predictor available up to time $t - 1$ and the corporate bond market returns observed until time t to estimate these coefficients. In terms of the next return forecast, while holding the starting point fixed, we expand our estimation window by incorporating the new information available at month $t + 1$ and calculate the return forecast using the updated predictive regression. This process ensures that all forecasts are generated in real time, i.e., only the information available at the time that forecasts are produced is used to generate the out-of-sample return forecasts. We repeat this procedure for every month until the sample is exhausted in December 2022.

Since individual predictors may contain specific information about the current state of the economy as well as substantial noise, we follow [Hollstein & Prokopczuk \(2023\)](#) and [Rapach et al. \(2010\)](#) to utilize information across individual forecasts via the forecast combination. The mean combination forecast is the equal-weighted average of the individual forecasts that uses the information of all predictors:

$$\text{COMB}_{t+1|t} = \frac{1}{N} \hat{r}_{1,t+1|t} + \frac{1}{N} \hat{r}_{2,t+1|t} + \cdots + \frac{1}{N} \hat{r}_{N,t+1|t}. \quad (3)$$

To evaluate the out-of-sample forecasting performance, we use the out-of-sample R^2 statistic of [Campbell & Thompson \(2008\)](#):

$$R_{OOS}^2 = 1 - \frac{MSPE_{Fore}}{MSPE_{Bench}} = 1 - \frac{\sum_{t=m}^{T-1} \left(r_{t \rightarrow t+1} - \hat{r}_{t \rightarrow t+1|t}^{Fore} \right)^2}{\sum_{t=m}^{T-1} \left(r_{t \rightarrow t+1} - \hat{r}_{t \rightarrow t+1|t}^{Bench} \right)^2}, \quad (4)$$

where $\hat{r}_{t \rightarrow t+1|t}^{Fore}$ is either an individual forecast based on the univariate predictive regression model or a combination forecast, $\hat{r}_{t \rightarrow t+1|t}^{Bench}$ is the historical average benchmark calculated as $\frac{1}{t-1} \sum_{\psi=1}^{t-1} r_{\psi \rightarrow \psi+1}$, t is the time that the forecast is made, T is the number of observations in the sample, and m denotes the start of the out-of-sample forecast evaluation period. A positive (negative) R_{OOS}^2 indicates that the $\hat{r}_{t \rightarrow t+1|t}^{Fore}$ forecasts outperform (underperform) the historical average forecasts in terms of the mean squared prediction error (MSPE) metric. We evaluate

the statistical significance of both in- and out-of-sample R^2 by using the bootstrap approach of Welch & Goyal (2008).

In addition, we apply the MSPE-adjusted statistic of Clark & West (2007) (CW) to compare forecasts made by nested linear models. The null hypothesis of the CW test is that the MSPE of the benchmark model is less than or equal to the MSPE of the competing predictive regression, i.e., $\hat{r}_{t \rightarrow t+1|t}^{Bench}$ encompass $\hat{r}_{t \rightarrow t+1|t}^{Fore}$. The MSPE-adjusted statistic is defined as follows:

$$f_{t \rightarrow t+1} = \left(r_{t \rightarrow t+1} - \hat{r}_{t \rightarrow t+1}^{Bench} \right)^2 - \left[\left(r_{t \rightarrow t+1} - \hat{r}_{t \rightarrow t+1|t}^{Fore} \right)^2 - \left(\hat{r}_{t \rightarrow t+1|t}^{Bench} - \hat{r}_{t \rightarrow t+1|t}^{Fore} \right)^2 \right]. \quad (5)$$

We next regress $f_{t \rightarrow t+1}$ on a constant and calculate the t -statistic of the constant. We use the standard normal distribution to obtain the one-sided (upper-tail) p -value of the null hypothesis.

Following Campbell & Thompson (2008) and Lin et al. (2018), we also evaluate the economic significance of corporate bond return forecasts. Specifically, we calculate the economic utility gains, or the certainty equivalent returns, for a mean-variance utility investor who allocates her wealth by either using the predicted market returns obtained from the out-of-sample forecast or ignoring such predictability. At time t , the investor who predicts the corporate bond returns will allocate her wealth to risky bond with the *ex ante* optimal weight $w_t^* = (1/\gamma)(\hat{r}_{t+1|t}/\hat{\sigma}_{t+1|t}^2)$, where γ is the coefficient of relative risk aversion that is set equal to five, and $\hat{\sigma}_{t+1|t}^2$ is the estimate of the variance of bond market returns. We proxy the variance forecast by using the historical bond market return data available at time t . Following Lin et al. (2018) and Thornton & Valente (2012), we restrict the optimal weight between zero (the short-sale constraint) and five. The economic utility gain of the investor is given by $CER = \hat{\mu}_p - (\gamma/2)\hat{\sigma}_p^2$, where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the mean and variance, respectively, of returns of portfolio formed using either an individual bond return forecast based on the univariate predictive regression model or a combination forecast over the out-of-sample period. To measure the economic significance between the portfolio choices, we calculate the $\Delta CER = CER_{model} - CER_{bench}$, where CER_{model} and CER_{bench} are the certainty equivalent returns implied by the forecast model and the benchmark model, respectively. Here we use the historical average forecast as the benchmark model.

3.2 Predictability analysis

To understand the role of each variable in return prediction, we first run predictive regressions of future returns for the corporate bond market against individual predictors. As shown in Panel A of Table 2, 10 out of 15 predictors (DP, DY, DE, SVAR, BM, LTR, TMS, DFY, INFL,

and IK) have statistically significant predictive power for market excess returns at the 5% level as indicated by both the NW and Hodrick t -statistics. The economic magnitude of the slope estimates is also sizable, ranging from -0.292% to 0.396%. For example, a one-standard-deviation increase in DP, DE, and DFY results in a 0.336%, 0.396%, and 0.388% increase in the subsequent return on the corporate bond market, respectively. A one-standard-deviation increase in INFL and IK also indicates a decrease in the market returns of -0.199% and -0.292%, respectively. In Table 1, we observe that the average corporate bond market portfolio return is 0.32% per month. Therefore, our results indicate that these predictors play an important role in predicting the average market portfolio returns. In addition, the in-sample R^2 statistics produced by 10 aforementioned predictors are economically large, ranging from 1.359% (INFL) to 5.343% (DE), and statistically significant at the 5% level as evaluated by the bootstrap approach of Welch & Goyal (2008). These sizable R^2 values also indicate that traditional predictors contain a significant amount of information about the time variation of the corporate bond market returns.

The previous in-sample forecasting tests focus on the statistical significance of the predictive coefficients by employing the entire historical sample. However, the variables that perform well in-sample do not automatically have good out-of-sample predictive performance. As argued by Welch & Goyal (2008), although many well-documented predictors are able to predict stock returns in-sample, they fail to consistently beat the simple historical average forecast in the out-of-sample prediction. We thus follow Lin et al. (2018), Welch & Goyal (2008), Rapach et al. (2010), and many others to conduct the out-of-sample tests from the perspective of an investor who forecasts corporate bond market returns based on the past and current available information only. Such tests also avoid the over-fitting problem and look-ahead bias, and thus contribute to testing the reliability and stability of the predictive power of return predictors.

We next generate the out-of-sample return forecasts recursively. The initial in-sample estimation period is from January 1986 to January 1991 containing 5 years of observations, and the out-of-sample evaluation period starts in February 1991 and ends in December 2022, with a total of 383 observations. Figure 1 plots the time series of corporate bond market return forecasts based on the 15 individual predictive regression models along with the mean combination forecast and historical average over the out-of-sample period. Similar to findings in the equity markets (e.g., Rapach et al., 2010), the return forecasts generated by individual predictive regression models are highly volatile and sometimes imply implausibly negative values for the

expected corporate bond market returns. To be specific, the individual forecasts tend to contain more noise and thus produce many false signals for return prediction. On the other hand, the mean combination forecast and historical average are more stable than the individual forecasts over time and show more plausible fluctuations. Compared to the historical average, the mean combination forecast exhibits better adaptive ability to changes in market and economic conditions, highlighting its ability to yield sizable statistical and economic benefits.

According to the sixth and seventh columns of Table 2, we find that only 4 out of 15 predictors consistently outperform the historical average forecast as evaluated by both the bootstrap approach of Welch & Goyal (2008) and the MSPE-adjusted statistics. Specifically, individual predictive models with DE, LTR, TMS, and DFY generate positive R_{OOS}^2 , ranging from 1.337% to 3.711%. These R_{OOS}^2 values are statistically significant at the 1% level (bootstrapped p -value = 0.00). Moving to the CW tests, these four models also generate positive MSPE-adjusted statistics with values from 1.961 to 2.465, indicating that they yield significantly lower MSPE than the historical average forecast at the 5% level. Turning to the results for the mean combination forecast in Panel B of Table 2, we find that the combination forecast generates an economically large R_{OOS}^2 of 1.641% with a MSPE-adjusted statistic of 3.153, which are both statistically significant at the 1% level. Therefore, it produces a lower mean prediction error than the historical average benchmark. Consistent with findings in equity markets (Rapach et al., 2010; Stock & Watson, 1998), our results imply that the mean combination method delivers significant out-of-sample forecasts of the corporate bond market return.

Why the out-of-sample performance of individual predictors is largely inconsistent with the in-sample results? Rapach et al. (2010) and Welch & Goyal (2008) emphasize the impact of structural instability in the relationships between the corporate bond market returns and individual macroeconomic and financial variables. In Figure 2, we plot the correlations between corporate bond market excess returns and individual predictors based on 5-year rolling windows. The correlations fluctuate substantially over the full sample period. For example, the correlation between INFL and corporate bond market returns is either negative or insignificant before the 2008 Global Financial Crisis, while it turns to be positive during the post-crisis period. Furthermore, the correlations between predictors and the market change from being significant during certain periods to being insignificant in others (see, e.g., BM, LTR, TMS, and DFR subplots). This implies a strong feature of structural instability within these relationships. Overall, consistent with the evidence from the literature on equity risk premium prediction (Paye &

Timmermann, 2006; Rapach & Wohar, 2006; Rapach et al., 2010), structural instabilities in individual predictive regression models partially account for the success of forecast combination in predicting returns of the corporate bond market portfolio.

Figure 3 illustrates the squared forecast bias and the forecast variance over the out-of-sample period for the 15 individual predictive regression models, the historical average, and the mean combination forecasts. Strikingly, compared to all individual predictive regression model forecasts, the mean combination forecast has the lowest level of variance and its forecast bias is lower than 11 out of 15 individual models. In addition, the variance of the mean combination forecast is moderately above that of the historical average forecast, while it generates a forecast bias that is noticeably lower than the historical average. This evidence is consistent with the out-of-sample analysis in which the mean combination forecast is able to generate more accurate return prediction with lower MSPE relative to the historical average. Rapach et al. (2010) first attributes this improvement to the ability of the combining method to reduce the noise in the individual model forecasts (i.e., lower variance). Also, it reflects the fact that the combining method incorporates information from a set of macroeconomic and financial variables in addition to the historical average method (i.e., smaller bias).

In the last column of Table 2, we report the economic utility gains (in annualized percentage return) for a mean-variance investor to assess the economic value of the predictability from an asset allocation perspective. Among all individual predictive models, half of them are able to deliver positive CER gains, ranging from 0.064% to 1.767%, over the out-of-sample period. The utility gain associated with the mean combination forecast is also economically large at 1.267%, which is higher than 14 of the 15 individual predictive regression models. In other words, the investor is willing to pay an annual portfolio management fee of 1.267% to switch from the historical average forecast to the mean combination forecast. These results align with the significant statistical performance and suggest that predicting corporate bond market returns has substantial economic gains for risk-averse investors.

Taken together, our findings point to the predictability of individual predictors and highlight the role of the combination forecast in providing more accurate and economically meaningful return forecasts. This provides direct motivation for us to examine the value of conditioning information in timing the corporate bond market.

4 Market Timing

4.1 Strategy

The economic intuition of market timing is to increase exposure to the corporate bond market portfolio in good times while decreasing exposure during bad times. Therefore, the timing weights in the managed corporate bond market portfolio should be proportional to the market return forecasts. Following [Hollstein & Prokopczuk \(2023\)](#), we apply the adjusted combination forecasts as the weights in the corporate bond market portfolio.

First, we conditionally demean the return forecasts by using the information available up to time t . This process helps to make the managed portfolio to be largely orthogonal to the market portfolio on average. It also alleviates the concern that the average exposure of the managed portfolio to the corporate bond market is the main driver of its returns ([Hollstein & Prokopczuk, 2023](#)). In real time, investors can obtain their desirable market exposure by combining the timing strategy with the plain corporate bond market portfolio. Second, we scale the weights in the managed market portfolio to match its conditional standard deviation with that of the corporate bond market portfolio, using only the information available at time t . This adjustment ensures that the performance of the managed market portfolio is comparable to that of other strategies. Overall, the time-series average of investment in the managed market portfolio implied by the timing strategy is approximately zero.

We define the timing weight in the managed corporate bond market portfolio as follows:

$$w_t^{\text{COMB}} = \delta_t \left(\text{COMB}_{t+1|t} - \frac{1}{H_t} \sum_{j=1}^t \text{COMB}_{j+1|j} \right), \quad (6)$$

where δ_t is chosen to exactly match the conditional standard deviation of the timing strategy with that of the corporate bond market portfolio, H_t is the total number of observations available at time t .⁹

Figure 4 plots the time series of the weights in the managed corporate bond market portfolio implied by the timing strategy. As can be seen from the figure, the weight is time-varying and fluctuates substantially around episodes of recessions. Specifically, we observe a decreasing pattern of the timing weight before and during the recessions, while it tends to rise dramatically

⁹ We conditionally demean the timing weight at each point in time recursively, and use the first 10 return forecasts to calculate the first demeaned combination forecast. The results based on alternative windows (e.g., 60 and 120 months) to help start the demeaning are qualitatively the same and available from the author upon request.

at the beginning of expansion periods. This feature underscores the ability of the combination forecast, which incorporates conditioning information extracted from various macroeconomic and financial variables, to signal changes in the investment and consumption opportunity set. Our findings in the corporate bond market are consistent with those in the equity market (Hollstein & Prokopczuk, 2023) and indicate the role of macroeconomic information in predicting business cycles (Gómez-Cram, 2022).

4.2 Performance of the timing strategy

To examine the performance of the timing strategy, in Figure 5, we compare the cumulative returns of a plain corporate bond market strategy (financed with the one-month risk-free assets) to a strategy augmented with the combination forecast-managed market portfolio. Specifically, we combine the plain corporate bond market portfolio with a conditionally demeaned investment in which the weights are implied by the out-of-sample market return combination forecasts (Figure 4). By doing so, two strategies invest approximately 100% in the corporate bond market portfolio on average over time. We assume that both strategies start with an initial investment of one unit dollar in December 1991. The figure shows that the strategy enhanced by the managed corporate bond market portfolio performs substantially well according to the cumulative wealth. In particular, a plain corporate bond market strategy with an initial wealth of 1\$ generates 3.15\$ at the end of 2022, whereas the combination forecast-managed market portfolio strategy yields a final cumulative wealth of 12.55\$. Furthermore, the superior performance of the managed market portfolio strategy was more noticeable after the Dot-com recession in 2001. We also observe that this strategy outperforms the buy-and-hold strategy substantially in the early phases of expansions, highlighting the role of combination forecasts in capturing favourable changes in market conditions.

In Panel A of Table 3, we report the results for the combination forecast-managed corporate bond market portfolio. Although the managed portfolio is largely orthogonal to the corporate bond market with approximately zero average exposure, it still generates an economically large mean excess return of 4.932% per year, which is statistically significant at the 5% confidence level. Hence, our results indicate that the predictability of the corporate bond market translates to significant economic gains for investors who utilize the timing strategy with information from market return combination forecasts.

Seeking to ascertain whether the profitability of the timing strategy can be explained by

existing corporate bond risk factors, we regress returns of the combination forecast-managed corporate bond market portfolio on that of other risk factors:

$$MKTB_t^{\text{Managed}} = \alpha_t + \beta' \mathbf{F}_t + \varepsilon_t, \quad (7)$$

where $MKTB_t^{\text{Managed}} = w_{t-1}^{\text{COMB}} \cdot MKTB_t$ is the return of the timing strategy in month t , $MKTB_t$ is the excess return of the corporate bond market portfolio, and $\mathbf{F}_t$ is a vector of risk factors. The variable of interest is α_t , which indicates whether the exposure to risk factors can explain the average returns of the managed portfolio implied by the timing strategy. A statistically significant alpha means that incorporating a managed corporate bond market portfolio into an investment opportunity set is beneficial to investors. This also indicates that an investor can build a tangency portfolio implied by a model expanded by the managed market portfolio with a higher Sharpe ratio than the original model (Barillas et al., 2020).

We consider a large set of factor models to evaluate the risk-adjusted performance:

1. The bond capital asset pricing model (CAPMB) of Dickerson, Mueller, & Robotti (2023), including the MKTB.
2. A one-factor model with the PEADB of Nozawa et al. (2024).
3. A two-factor model (BOND2) with the MKTB and PEADB factors.
4. A two-factor model with two market factors (MKT2), including the MKTB and the excess equity market returns (MKTS).
5. The intermediary asset pricing model (HKM) of He et al. (2017), including the MKTS and a traded financial intermediary factor.
6. A two-factor model with the default and term structure factors (FF2) of Fama & French (1993).
7. A five-factor model (BOND5) in the spirit of Bali et al. (2021), including the MKTB, PEADB, LTR, MOMB, and STR factors.
8. A five-factor model (IPR5) in the spirit of Israela et al. (2018), featuring the CRY, DUR, MOMB, VAL, and MOMS factors.
9. A five-factor model (STOCK5) with five equity risk factors, including the MKTS, SMB, HML, MOMS, and LIQ factors, following Fama & French (1993), Carhart (1997), and Pástor & Stambaugh (2003).
10. The Fama & French (1993) five-factor model for corporate bonds (FF5), including the DEF, TERM, MKTS, SMB, and HML factors.

11. A six-factor model (BS) with equity and corporate bond risk factors, including MKTB, MKTS, SMB, HML, MOMS, and LIQ factors.
12. A six-factor model (STOCK6) with six equity risk factors, including MKTS, SMB, HML, MOMS, RMW, CMA factors, following [Fama & French \(2015\)](#) and [Carhart \(1997\)](#).
13. A seven-factor model (BS7) constructed by adding the MKTB to the STOCK6.
14. A ten-factor model (BS10), combining the BOND5 with the FF5.

The performance of the timing strategy in a cross-sectional setting is summarized in Panel B of Table 3. We first investigate the explanatory power of the CAPMB on the return for the managed corporate bond market portfolio. As indicated by the loading on the corporate bond market factor, the combination forecast-managed portfolio has a significant positive market exposure of 0.513 (t -statistic = 2.44). Nevertheless, the risk-adjusted return of the managed portfolio after controlling for the CAPMB is economically sizable about 2.942% per year and statistically significant at the 5% level with a [Newey & West \(1986\)](#) t -statistic of 2.22. The single-factor CAPMB plays an important role in understanding expected corporate bond returns as it has nontrivial pricing ability and is not dominated by low dimensional factor models in the literature ([Dickerson, Mueller, & Robotti, 2023](#)). Thus, our evidence directly suggests that the managed market portfolio improves investors' investment opportunity set beyond that characterized by the CAPMB.

Next, we evaluate the performance of the managed corporate bond market portfolio after controlling for other factor models. Across various candidate models, none of them are able to explain the average returns of the managed portfolio as indicated by sizable annualized alphas ranging from 2.988% to 6.370%, which are all statistically significant at the 5% level. For example, although the managed portfolio loads significantly negatively on the PEADB, it strikingly generates an economically large abnormal return of 6.370% per year with a t -statistic of 2.80. Taken together, our results not only highlight the distinct role of time-series predictability in enhancing investment performance, but also motivate us to further incorporate the managed market portfolio into the optimal portfolio choice problem.

4.3 Performance of enhanced strategies

Given the strong performance of the managed corporate bond market portfolio, in this subsection, we evaluate the outcomes of enhanced strategies. That is, we compare the optimal portfolios of the space spanned by factors of pricing models alone with the optimal combina-

tion portfolios in which the model space is augmented by the managed corporate bond market portfolio. Following [Cederburg et al. \(2020\)](#), we consider a mean-variance investor who allocates wealth between excess returns of original N_f factor strategies $\mathbf{f}_t = [f_{1,t}, \dots, f_{N_f,t}]$ and the managed corporate bond market strategy $f_{M,t}$. The investor's optimal weight allocated to the managed market factor and original factors in the vector form is given by $s = [x_M^*, x_1^*, \dots, x_{N_f}^*]'$, which is the solution of the following maximization problem:

$$\max_s U(s) = s' \hat{\mu} - \frac{\gamma}{2} s' \hat{\Sigma} s, \quad (8)$$

where $\hat{\mu} = [\bar{f}_{M,t}, \bar{f}_{1,t}, \dots, \bar{f}_{N_f,t}]$ denotes a vector of average excess returns, γ is the investor's risk aversion parameter, and $\hat{\Sigma}$ is a $(N_f + 1) \times (N_f + 1)$ variance-covariance matrix. This setup implicitly assumes that investors have access to the risk-free asset. Accordingly, the vector of optimal portfolio weight is specified as:

$$s = \frac{1}{\gamma} \hat{\Sigma}^{-1} \hat{\mu}. \quad (9)$$

Here the weights in the $(N_f + 1)$ risky assets depend on the investor's risk aversion. Similar to [Cederburg et al. \(2020\)](#), we consider a risk aversion parameter of $\gamma = 5$ and impose a leverage constraint by which the sum of the risky assets' absolute weights in the optimal strategy is smaller than or equal to five.¹⁰ In addition, we also consider a tangency portfolio with a vector of optimal relative weights in the $(N_f + 1)$ risky assets given by:

$$s^r = \frac{\hat{\Sigma}^{-1} \hat{\mu}}{\mathbf{1}' \hat{\Sigma}^{-1} \hat{\mu}}, \quad (10)$$

where $\mathbf{1}$ is a $(N_f + 1) \times 1$ vector of ones. Here the relative allocations across the risky assets are independent of the investor's risk preferences.

In Panel A of Table 4, we present the full-sample results. Combining the managed corporate bond market portfolio with the CAPMB increases the in-sample Sharpe ratio of the optimal portfolio by 0.116 (from 0.648 for the static bond market portfolio to 0.764 for the optimal one). Also, this optimal portfolio has an optimal relative weight allocated to the managed market portfolio of 41.2%. Relative to the other factor models, incorporating the managed market portfolio into the investment opportunity set consistently improves the in-sample Sharpe ratio of the optimal portfolio, with the difference in Sharpe ratios ranging from 0.069 (BS7) to 0.283 (PEADB).

¹⁰ The results for a risk aversion level of three are qualitatively similar and are available from the author upon request.

However, the investment outcomes suggested by the in-sample portfolio choice tests are not implementable in real time. [Cederburg et al. \(2020\)](#) find that when investors form trading strategies conditional only on past information, the observed performance of the volatility-managed portfolio significantly differs from the *ex post* results. One possible reason is the estimation risk in the real-time portfolio choice exercises since the optimal weights may fluctuate dramatically over time, resulting in the poor out-of-sample performance of the optimal portfolio ([Black & Litterman, 1992](#); [Cederburg et al., 2020](#); [DeMiguel et al., 2009](#); [Jagannathan & Ma, 2003](#)). Given this concern, we examine the performance of optimal portfolios in an out-of-sample setting to assess the implication of timing strategy for real-time mean-variance investors. That is, we estimate the optimal investment weights in the out-of-sample combination portfolio by using the data available up to time t . To do so, we follow [Cederburg et al. \(2020\)](#) and use an expanding-window approach. We start with a sample of T monthly return observations for a given factor model and the managed market portfolio. We consider an initial estimation period (K) of 120 months and evaluate the real-time performance over the out-of-sample period of $T - K$ months. At each point in time, we calculate the relevant portfolio parameters and weights in the optimal combination strategy in the next month, using information from this past window. This design entirely alleviates the concern of look-ahead bias and is implementable for real-time investors who rely on past data in portfolio construction.

To assess the performance of optimal combination strategies in real-time, we examine whether these enhanced strategies improve investment outcomes relative to portfolios without the managed market factor. Our first evaluation metric is the Sharpe ratio difference defined as follows:

$$\Delta SR_{OOS} = \frac{\hat{\mu}_i}{\hat{\sigma}_i} - \frac{\hat{\mu}_j}{\hat{\sigma}_j}, \quad (11)$$

where $\hat{\mu}_i$ and $\hat{\sigma}_i$ denote the mean and standard deviation, respectively, of excess returns for the strategy with allocations to the managed corporate bond market portfolio, original factor portfolio, and the risk-free asset (the optimal combination strategy) over the out-of-sample evaluation period. Similarly, $\hat{\mu}_j$ and $\hat{\sigma}_j$ denote the mean and standard deviation, respectively, of excess returns for the strategy with allocations to the original factor portfolio and the risk-free asset. To test whether the Sharpe ratio difference is statistically significant, we use the [Jobson & Korkie \(1981\)](#) test with a null hypothesis $H_0 : \Delta SR = 0$.

Second, we follow [Fleming et al. \(2001\)](#) and estimate the relative utility gain (Utility, Δ) of the optimal combination strategy relative to strategies without the managed market portfolio

for investors with constant relative risk aversion of $\gamma = 5$. In particular, we compute the value of Δ that satisfies

$$\sum_{t=K}^{T-K-1} (R_{OC,t+1} - \Delta) - \frac{\gamma}{2(1+\gamma)} (R_{OC,t+1} - \Delta)^2 = \sum_{t=K}^{T-K-1} R_{t+1} - \frac{\gamma}{2(1+\gamma)} R_{t+1}^2, \quad (12)$$

where $R_{OC,t+1}$ and R_{t+1} represent the returns for the optimal combination and original factor strategies, respectively. This equation implies that holding an original factor strategy achieves the same utility gain as holding the optimal combination strategy after accounting for a fraction of wealth invested Δ . Following [Fleming et al. \(2001\)](#), we interpret the Utility as the annualized maximum performance fee that an investor would be willing to pay to switch from the original factor strategy to the optimal combination strategy.

Panels B and C of Table 4 show results from out-of-sample tests for 14 factor strategies. We find that all managed market portfolio-enhanced strategies outperform original factor models by delivering positive and significant increases in the annualized Sharpe ratio, ranging from 0.053% to 0.348%. For instance, the annualized Sharpe ratio of the enhanced MKT2 strategy increases by 0.256 (from 0.295 for the original factor model to 0.551) with a p -value of 0.004. The managed market portfolio also takes a considerable position in the enhanced strategy with an average optimal weight of 67.5%. Moreover, adding the managed portfolio into the investment opportunity set provides pronounced utility gains for investors. Across all enhanced factor strategies, the relative utility gains are positive and economically large, with annualized Utility ranging from 0.664% to 5.282%. That is, the investor is willing to pay an annual performance fee of up to 5.282% to switch from a plain factor strategy to an enhanced one. Next, we obtain consistent results by using the tangency portfolio approach in which the relative optimal weights are independent of investors' risk preferences. We find that the differences in the Sharpe ratio are positive and statistically significant for all combination strategies. In addition, these enhanced strategies are favourable to investors as they generate positive utility gains, although their magnitude is relatively smaller than that under the [Cederburg et al. \(2020\)](#)'s approach.¹¹

Without using portfolio optimization methods, we also consider the naive 1/N approach for the factor models and enhanced strategies. We summarize the results in Panel C of Table 4. We notice that 12 out of 14 enhanced strategies are able to generate positive Sharpe ratio differences. The failure of remaining enhanced strategies could be attributed to the over- or under-weight of

¹¹ Note that two out-of-sample strategies yield the same relative weights on factors and the managed market portfolio in the optimal combination strategy for a mean-variance investor, whereas the absolute weight assigned by the [Cederburg et al. \(2020\)](#)'s approach is influenced by the level of investors' risk preferences.

the managed market portfolio. For example, the optimal portfolio choice assigns 15.6% weight to the managed portfolio for the enhanced CAPMB, whereas the 1/N approach allocates a much larger weight of 50% on that. Therefore, even if the managed portfolio alone is economically important, optimally conducting the portfolio choice exercise adds more value to the investment outcomes of investors in real time.

To conclude, our findings point to significant improvements in using the managed corporate bond market portfolio in an out-of-sample setting. This further illustrates that timing the corporate bond market with combination return forecast is not confined to in-sample success, but has great implications for real-time investors in optimal portfolio choices.

4.4 Timing by single predictors

Having established the performance of the combination forecast-managed corporate bond market portfolio, we next investigate the timing ability of each macroeconomic and financial predictor. By doing so, we calculate the weight in the bond market portfolio by using either the past realizations or the return forecasts made by each predictor. Similar to our main empirical analysis, we conditionally demean the timing weights and scale the conditional standard deviation in the managed portfolio to be equal to that of the corporate bond market portfolio. Finally, a single factor-managed portfolio is constructed as $MKT B_t^{Predictor} = w_{t-1}^{Predictor} \cdot MKT B_t$, where $w_{t-1}^{Predictor}$ is the weight corresponding to each predictor.

Table 5 shows the average returns and alphas for managed bond market portfolios constructed by using prior realizations of predictors as the weights. Timing portfolios managed by TBL, LTY, LTR, TMS, INFL, and IK yield statistically significant average returns, ranging from 2.389% to 4.687% per annum in absolute terms.¹² Moreover, in terms of risk-adjusted returns, five predictors (BM, LTR, TMS, INFL, and IK) generate alphas that are statistically significant relative to half of the candidate factor models. Furthermore, Table 6 reports the results for predictor forecast-managed market portfolios. We find that most conditioning predictors' forecasts used alone cannot generate economically meaningful managed portfolios with statistically significant average returns. In particular, five out of 15 predictors (DP, DY, BM, LTR, and IK) yield average returns of the managed portfolio that are significantly different from zero. For example, BM and IK-managed portfolios have annualized average returns of 4.548% and 5.154%, respectively, which are highly significant at the 1% level. However, only three

¹² There are negative returns for managed market portfolios since some predictors negatively forecast the corporate bond market portfolio.

variables (BM, LTR, and IK) generate significant alphas after accounting for at least half of the candidate factor models. Generally, these pieces of evidence from the performance of individual predictor-managed portfolios are consistent with those from the time-series predictability (see Section 3.2). That is, individual variables may contain substantial noise in predictability and thus perform poorly in adding value for timing the corporate bond market. The combination forecast, on the other hand, possesses the ability to aggregate information contained in many different predictors, translating to noticeable economic gains earned in real-time market timing. Interestingly, among all predictors, interest rates and financial ratios tend to contain more information in managing the corporate bond market.

4.5 Turnover and transaction costs

Our preceding analysis establishes the economically significant gains for investors who utilize combination return forecasts to manage the corporate bond market portfolio. However, dynamic trading strategies involve time-varying weights, thus are associated with transaction costs for the turnover of the holdings. In this subsection, we appraise the impact of transaction cost on the performance of the managed bond market portfolio.

To do so, we first compute the turnover rate (TO) of the timing strategy as the time-series average of all re-balanced trades incurred as follows:

$$TO = \frac{1}{T-1} \sum_{t=1}^{T-1} (|w_{t+1}^{\text{COMB}} - w_t^{\text{COMB}}|), \quad (13)$$

where w_t^{COMB} is the timing weight in month t . In addition, we calculate the net return of the timing strategy as follows:

$$\overline{MKT B}_{t+1}^{\text{Managed}} = MKTB_{t+1}^{\text{Managed}} - TC |\tilde{w}_t^{\text{COMB}} - \tilde{w}_{t-1}^{\text{COMB}}|, \quad (14)$$

where $\overline{MKT B}_{t+1}^{\text{Managed}}$ is the net return of the timing strategy in month $t+1$, and $MKT B_{t+1}^{\text{Managed}}$ represents returns to the managed portfolio with an estimated timing weight $\tilde{w}_t^{\text{COMB}}$ in month t . We calculate the break-even proportional transaction cost (in bps) which leads to zero net return. We also set the proportional trading cost (TC) to 1, 5, 10, and 15 basis points (bps), respectively, to assess the performance of managed portfolio after accounting for the transaction costs.

In Panel A of Table 7, the turnover rate of the managed corporate bond market portfolio is modest at 0.347. An estimate of break-even transaction costs indicates that the extra cost

per trade that would be required to wipe out average returns for the managed market portfolio equals 119 bps. Furthermore, after accounting for the proportional transaction costs, investment in the managed bond market portfolio is still attractive to investors. For example, as illustrated in Panel B, after subtracting four different levels of transaction cost, the average returns of the managed portfolio range from 4.308% to 4.890% per year, all of which are significant at the 5% level. On a risk-adjusted basis, the alphas relative to 14 factor strategy portfolios are all positive and economically large, confirming that transaction costs subsume a relatively small proportion of the performance of managed portfolios. Finally, we evaluate the utility gains of enhanced strategies after considering the transaction costs. Results suggest that investors are still better off by taking an investment strategy to incorporate the managed bond market into original factor strategies. For example, with a conservative transaction cost of 15 bps, all enhanced strategies generate positive utility gains ranging from 0.284% to 3.595%, except for the BS7.

Overall, the performance of the combination forecast-managed corporate bond market portfolio is robust after considering the impact of transaction cost and adds economic value for investors. As the corporate bond databases (e.g., ICE and TRACE), market portfolio data, and return predictors are readily available for investors, they can easily implement the market timing strategy based on the combination return forecasts. As noted by [Lin et al. \(2018\)](#), the corporate bond market is dominated by institutional investors who are more sophisticated and have more resources to implement the investment strategy with higher efficiency and lower costs. For retail investors, there are many exchange-traded funds (ETFs) that effectively track the corporate bond market indexes with low trading costs.¹³ Therefore, strategies based on timing the corporate bond market are accessible to investors and have great implications for their investment outcomes.

4.6 Combining forecasts with time-varying weights

We next consider an alternative way to determine the weights in the corporate bond market portfolio. Following [Rapach et al. \(2010\)](#), we use the discount mean square prediction error

¹³ For example, the SPDR Portfolio Corporate Bond ETF (SPBO) has a total asset value of about 1.4 billion dollars and tracks the Bloomberg Corporate Bond Index with an expense ratio of 3 bps. The iShares Broad USD Investment Grade Corporate Bond ETF (USIG), which tracks the Merrill Lynch Aggregate Bond Market index, has a total asset value of around 10 billion dollars and an expense ratio of 4 bps. Although the corporate bond market is relatively illiquid, the bond index trackers usually adopt a sampling strategy to effectively track the market portfolio while maintaining a lower level of transaction costs ([Dick-Nielsen & Rossi, 2019](#)). It is worth noting that the correlations between the market portfolio used in the main analysis and these two market indexes are all above 96%. In the robustness checks, we show that the managed portfolios based on these alternative proxies of market portfolios perform consistently well.

(DMSPE) combining method of [Stock & Watson \(2004\)](#), in which the timing weights of individual forecasts formed at time t are determined by the historical forecasting performance of that predictor over the out-of-sample evaluation period. In other words, this method assigns a higher weight to predictors with greater historical performance. In particular, the timing weights are expressed as follows:

$$w_{i,t} = \phi_{i,t}^{-1} / \sum_{p=1}^N \phi_{p,t}^{-1}, \text{ where } \phi_{i,t} = \sum_{q=m}^{t-1} \theta^{t-1-q} (r_{q+1} - \hat{r}_{i,q+1})^2. \quad (15)$$

Here θ is a discount factor, which is set equal to 0.9. When θ is smaller than 1, the DMSPE approach places higher weight on the recent forecast accuracy of individual forecasts.¹⁴

Table 8 reports the results of applying the DMSPE combining method. As shown in Panel A, the time-series evaluation tests produce an out-of-sample R^2 of 2.043%, which is statistically significant at the 1% level (p -value = 0.00). The out-of-sample predictability also generates an annualized economic utility gain of 1.984% for a mean-variance investor. Moving to the DMSPE combination forecast-managed market portfolio (Panel B), we find that all factor alphas are economically large ranging from 3.041% to 5.731% and statistically significant at the 10% level or better. In Panel C of Table 8, we summarize results for the performance of enhanced strategies. Noticeably, adding the DMSPE combination forecast-managed market portfolio to original factor strategies generates positive Sharpe ratio gains in all cases. From the perspective of real-time combination, such improvements are also consistent with the in-sample evidence. For example, based on the [Cederburg et al. \(2020\)](#)'s approach (Panel C.2), the Sharpe ratio differences for enhanced strategies range from 0.112 (p -value = 0.027) to 0.331 (p -value = 0.000), all significant at the 5% level. Meanwhile, the relative utility gains are also positive and economically large, ranging from 1.254 to 6.330. Similar results are obtained when we turn to the optimal tangency portfolios. To sum up, our results further corroborate the role of managed corporate bond market portfolio in providing more favourable investment opportunities for investors.

4.7 Imposing leverage constraints

Previous analysis shows that the timing weights vary substantially over time and link to business cycles (see Figure 4). In this subsection, we examine whether the performance of managed bond market portfolios is driven by extreme timing weights allocated to the corporate bond market portfolio by imposing leverage constraints. In particular, we restrict the w_t^{COMB} to the intervals

¹⁴ We obtain quantitatively similar results of setting $\theta = 1$, a scenario with no discounting.

of $[-4, 4]$, $[-3, 3]$, $[-2, 2]$, $[-1, 1]$, and $[0, 1]$. The last case corresponds to a timing strategy with a short-sale constraint and zero excess leverage. Table 9 provides results for the performance of managed market portfolio with leverage constraints. Overall, the statistical significance of the factor alphas remains unchanged by imposing a leverage constraint on portfolio positions. All risk-adjusted returns are still positive and statistically significant, implying that the extreme timing weight implied by the combination forecast is not the driving force behind our main results. This evidence suggests the potential for investors to scale the total investment by a constant proportion. It will also help to achieve a more desirable level of leverage taken without largely influencing the performance of a resulting portfolio.

5 Understanding the performance of market timing

In this section, we explore whether the forecasts of bond market returns are consistent with explanations based on the time-varying macroeconomic risk. We then examine an important implication of market timing to better understand the economic source of managed market portfolio performance.

5.1 Linking return predictability to variations in business conditions

We start our analysis by investigating the relation between our forecasts of excess bond market returns and changes in business conditions. Fama & French (1989) first show that expected corporate bond returns are associated with variations in economic conditions. A recent study of Lin et al. (2018) confirms Fama & French (1989)’s in-sample findings and suggests that the time-varying macroeconomic risk is the main force driving the bond return predictability. In Panel A of Figure 6, we plot the forecast of bond market returns obtained from the mean-combination method against the annual growth of industrial production index. It is clear that the expected bond market returns exhibit a strong countercyclical pattern. Specifically, the contemporaneous correlation between them is -38.5% (p -value = 0.00). Moreover, Panel B reveals a positive and statistically significant correlation of 37.6% (p -value = 0.00) between realized and expected bond market returns. A high contemporaneous correlation indicates the ability of combination forecasts to infer bond market returns. During economic recessions, both realized and predictive model-implied expected returns become more volatile, and the correlations between them tend to surge, indicating that both realized and expected returns can reflect time-varying economic fundamental risks. Overall, our findings echo previous studies and suggest that the forecasts of

corporate bond market returns are associated with variations in business conditions, implying the role of time-varying macroeconomic risk in driving return predictability.

5.2 Bond market timing and changes in economic and market states

The analysis above shows that macroeconomic and financial predictor variables contain important information for predicting corporate bond market returns, which are closely linked to variations in business conditions. In this subsection, we examine how the performance of bond market timing relates to changes in economic and market states to understand more about the economic implications of market timing.

The economic intuition of bond market timing is to dynamically manage the market portfolio exposure during good or bad times. Therefore, the timing strategy should perform more well in an environment in which the timing stands a better chance of capturing changes in economic and market states. To test this prediction, we consider a set of conditioning variables that proxy for the state of the economy and financial markets. To capture changes in economic conditions, we use five variables, including the industrial production growth, the Chicago Fed National Activity Index (CFNAI), the dividend-to-price ratio, the credit spread (calculated as the yield difference between Moody’s seasoned Baa corporate bonds and 10-year constant-maturity Treasury bonds), and the real interest rate (calculated as the difference between the US 3-month T-bill rate and expected inflation that is the 3-month moving average of changes in the US consumer price index). In addition, we also consider five uncertainty indicators to represent the market states. These variables are the macroeconomic and real uncertainty indexes of [Jurado et al. \(2015\)](#), the financial uncertainty index of [Ludvigson et al. \(2021\)](#), the economic uncertainty index of [Bekaert et al. \(2022\)](#), and the volatility index (VIX).¹⁵ In the spirit of [Maurer et al. \(2023\)](#), we apply the two-regime analysis and test the performance of combination forecast-managed market portfolio in periods of large versus small absolute changes in these conditioning variables. Specifically, we split the sample data into two subgroups with equal numbers of months, which correspond to times of large (above median) and small (below median) absolute changes in the conditioning variables.

Table 10 summarizes the performance of managed bond market portfolios while conditioning on large versus small changes in state variables. In Panel A, we find that the combination

¹⁵ The data for the macroeconomic conditioning variables and the VIX are collected from the FRED. Uncertainty data are downloaded from the website of Sydney C. Ludvigson: <https://www.sydneyludvigson.com/> and Nancy R. Xu: <https://www.nancyxu.net/>

forecast-managed portfolio performs consistently better in subsamples of large absolute changes in five conditioning variables that proxy economic conditions. For example, in times of large absolute changes in industrial production, the average return of managed bond market portfolio is 7.161% per year and statistically significant at the 5% level. After adjusting for a set of factor models, the alphas are still statistically significant and economically large, ranging from 4.463% to 8.212%. In contrast, when changes in industrial production are small, the alphas of managed portfolios are statistically insignificant in most cases. Moving to Panel B of Table 10, we obtain similar results that the timing strategy performs more successfully when changes in macroeconomic uncertainty, financial uncertainty, real uncertainty, economic uncertainty, and the VIX are large. For instance, conditional on large changes in economic uncertainty, the managed portfolio generates an annualized average return of 7.78% (t -statistic = 2.03). The risk-adjusted returns are also statistically significant after controlling for other factor models. As a comparison, almost all risk-adjusted returns of the managed portfolio conditional on small changes in economic uncertainty are statistically insignificant. Since absolute changes in these conditioning variables represent the time variation in the market environment, our findings support the testable implication that market timing is more beneficial when economic states are more volatile. Thus, we can attribute the outstanding performance of managed bond market portfolios to the ability of predictor variables to infer quickly changing market environments, helping the timing strategy to better capture time-varying risk premiums.

In summary, our empirical results suggest that changes in business conditions closely link to time variations in expected corporate bond market returns. As predictors used by [Welch & Goyal \(2008\)](#) perform well in tracking movements in economic fundamentals ([Boons, 2016](#)), this explains why these predictor variables are able to predict bond market returns. More strikingly, we show that managed bond market portfolios deliver more value in an environment in which the timing is more relevant, i.e., when economic and market conditions are rapidly changing over time.

6 Additional robustness checks

In this section, we perform several robustness tests to further show that our baseline results are not due to specific research design or sample selection.

6.1 Alternative corporate bond market proxies

Our first robustness check examines the performance of market timing by adopting three alternative proxies for the corporate bond market portfolio. First, the bond market portfolio is proxied by the Bloomberg US Corporate Bond Index covering the sample period from January 1986 to December 2022. Second, we consider returns of the Merrill Lynch Aggregate Bond Market index in excess of the one-month risk-free rate of return to represent the MKTB. The sample period starts from January 1986 to December 2022. Third, we use the corporate bond market factor constructed by using the TRACE database from the Wharton Research Data Services (WRDS) bond database. The sample period is from September 2002 to September 2022.¹⁶ We replicate Table 3 and summarize the results for using alternative market portfolio proxies in Panel A of Table 11. Consistent with the baseline results, different timing strategies with alternative corporate bond market proxies still deliver value to investors. For example, a managed portfolio based on the Bloomberg US Corporate Bond Index generates a positive and statistically significant average return of 4.509% per year (t -statistic = 2.69). The alphas relative to factor model strategies are also economically meaningful, ranging from 2.399% to 5.963%. In summary, these alternative changes in using market proxies do not impact the performance of managed portfolios and reinforce the predictability of corporate bond market.

6.2 Excluding specific periods

As observed in Figure 4 and 5, the timing weights and the returns of managed portfolio tend to be higher in the later phases of recessions, such as the 2008 global financial crisis and the COVID-19 pandemic periods. This is consistent with the economic intuition of market timing that invests more in good times and provides protection during bad times given the conditioning information. Therefore, we exclude these crisis periods during which the managed corporate bond market portfolio performs noticeably well and examine whether our results are driven by salient times. In particular, we first exclude January 2008 to June 2009, a period corresponding to the 2008 global financial crisis. Next, we further exclude the COVID-19 pandemic period from January 2020 to April 2020. The results are summarized in Panel B of Table 11. Although the magnitude of returns in crisis period is larger than that in non-crisis period, neither the average returns nor the alphas of the managed market portfolio are statistically significant in

¹⁶ The Bloomberg US Corporate Bond Index is collected from the Bloomberg. The Merrill Lynch Aggregate Bond Market index is obtained from the Federal Reserve Economic Data (FRED). The TRACE (WRDS)-based corporate bond market factor is obtained from <https://openbondassetpricing.com/>.

most cases. In contrast, managed bond market portfolios generate positive and statistically significant returns in non-crisis period, suggesting that our baseline results are not driven by extreme weights and returns concentrated in crisis times.

6.3 Alternative combination forecasts

Next, we follow [Rapach et al. \(2010\)](#) and consider alternative averaging schemes, including the median and trimmed-mean combination, to obtain the return forecasts. In particular, the median combination forecast is the median value of $\hat{r}_{1,t+1|t}$, where $i = 1 \cdots N$. The trimmed-mean combination forecast eliminates individual return forecasts with the highest and lowest values and then takes a simple average of remaining forecasts. The results when using alternative combination forecasts are presented in Panels C.1 to C.4 of Table 11. Similar to the results in [Lin et al. \(2018\)](#), we notice that the median combination forecast-managed market portfolio seems to have the worst performance, suggesting that the return forecasts across individual predictors are asymmetric. In addition, all trimmed-mean combination forecast-managed portfolios show superior performance in generating more sizable portfolio returns. This evidence indicates that the predictability of bond market return is not restricted to a small group of predictors with extreme return forecasts.

In addition, we also consider a binary timing strategy, which invests either 100% in the bond market portfolio when the conditioning variable exceeds its conditional mean or 0% in all other periods. In other words, we only take long positions in the bond market portfolio if the combination return forecast exceeds its conditional average. This strategy can be easily implemented by investors given the fact that it has relatively low transaction costs and does not involve leverage and short-sale trading. Panel C.5 of Table 11 shows that when using the binary timing strategy, the average and risk-adjusted returns for the managed market portfolio are smaller than those in the main specification. Although restricting leverage and short selling makes the performance less pronounced, the alphas relative to all factor models are positive and statistically significant.

6.4 Alternative estimation scheme

In our final robustness check, instead of using a 5-year recursive estimation approach, we consider alternative estimation schemes to produce market return forecasts. We present the results in Panel D of Table 11. First, we consider a relatively longer recursive estimation window of

120 months. We find that results shown in Panel C.1 continue to exhibit a significant and robust performance of the combination forecast-managed portfolio as all alphas relative to cross-sectional factor models are highly significant at the 5% level. Finally, in Panel C.2, when we employ a rolling window estimation scheme of a fixed length of 5 years, the results for the managed market portfolio are more pronounced. In particular, the average return of the resulting portfolio is 6.223% per year, which is highly significant with a t -statistic of 5.41. Meanwhile, the annualized risk-adjusted returns of the timing portfolio range from 5.924% to 6.937%, which are statistically significant at the 1% level. Since return forecasts generated by a rolling window scheme are more likely to reflect the instant movements in the relation between predictors and the bond market, it is not surprising that such an estimation method leads to better performance of the managed portfolio.

In summary, a battery of robustness checks suggests that the relation between time-series predictability and the market timing in corporate bond markets holds for alternative methodological design and data choices.

7 Conclusion

In this paper, we study timing strategies for the corporate bond market portfolio and examine whether they have potential benefits for real-time investors. Based on the standardized predictive regression model framework, we show that the corporate bond market portfolio is highly predictable, aligning with the predictability of stock returns. We employ the forecast combining method with 15 macroeconomic and financial predictor variables, and find convincing evidence of the in-sample and out-of-sample predictability of bond market returns over time. By leveraging the return predictability, we implement a timing strategy by dynamically adjusting the exposure to the bond market portfolio, i.e., to increase exposure in good times while reducing exposure during bad times. Thus, the investment position in the market portfolio is proportional to the excess return forecasts. We document that the resulting managed market portfolios with information from combination return forecasts offer significant risk-adjusted returns relative to a large set of existing factor models. In addition, optimal combination strategies of the managed market portfolio and original factor models exhibit strong in-sample performance, as indicated by improved in-sample Sharpe ratios ranging from 0.07 to 0.283. More importantly, results of the out-of-sample combination strategies show that the managed bond market portfolio can produce significantly improved annualized Sharpe ratios (up to 0.35%) and utility gains (up to 5.28%)

for mean-variance investors in a real-time investment setting. Therefore, timing the corporate bond market is not confined to merely an in-sample success.

To understand the economic mechanism driving the performance of the corporate bond market timing strategy, we first show that the time variations in expected corporate bond market returns are strongly associated with changes in business conditions. This is consistent with the time-varying macroeconomic risk channel driving the bond return predictability. Since the conditioning information set of macroeconomic and financial predictors is informative about variations in business conditions, the superior performance of the market timing strategy is a manifestation of such time-series predictability. Next, we perform a two-regime analysis and find that the market timing strategy offers more value during periods of rapid economic and market change. This implication further demonstrates a close link between market timing and time variation in economic conditions.

Taken all together, this paper highlights the important role of using conditioning information in managing the corporate bond market portfolio. Our results also add to the growing literature on AI-assisted investment strategies by showing how data-driven portfolio timing methods can improve financial decision-making in fixed-income markets without relying on black-box machine learning algorithms. Going forward, it might be fruitful to further explore the effect of timing strategy for other risk factors in corporate bond markets, and the implication of managed factors in corporate bond pricing studies.

References

- Andreani, M., Palhares, D., & Richardson, S. (2024). Computing corporate bond returns: A word (or two) of caution. *Review of Accounting Studies*, 29, 3887–3906.
- Ang, A., & Bekaert, G. (2007). Stock return predictability: Is it there? *Review of Financial Studies*, 20, 651–707.
- Arnott, R. D., Kalesnik, V., & Linnainmaa, J. T. (2023). Factor momentum. *Review of Financial Studies*, 36, 3034–3070.
- Atanasov, V., Møller, S. V., & Priestley, R. (2020). Consumption fluctuations and expected returns. *Journal of Finance*, 75, 1677–1713.
- Bakshi, G., Gao, X., & Rossi, A. G. (2019). Understanding the sources of risk underlying the cross section of commodity returns. *Management Science*, 65, 619–641.
- Bali, T. G. (2008). The intertemporal relation between expected returns and risk. *Journal of Financial Economics*, 87, 101–131.
- Bali, T. G., Beckmeyer, H., & Goyal, A. (2024). *A joint factor model for bonds, stocks, and options*. (Working Paper)
- Bali, T. G., Goyal, A., Huang, D., Jiang, F., & Wen, Q. (2022). *Predicting corporate bond returns: Merton meets machine learning*. (Working Paper)
- Bali, T. G., Subrahmanyam, A., & Wen, Q. (2021). Long-term reversals in the corporate bond market. *Journal of Financial Economics*, 139, 656–677.
- Barillas, F., Kan, R., Robotti, C., & Shanken, J. (2020). Model comparison with sharpe ratios. *Journal of Financial and Quantitative Analysis*, 55, 1840–1874.
- Barroso, P., & Detzel, A. (2021). Do limits to arbitrage explain the benefits of volatility-managed portfolios? *Journal of Financial Economics*, 140, 744–767.
- Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, 116, 111–120.
- Bekaert, G., Engstrom, E. C., & Xu, N. R. (2022). The time variation in risk appetite and uncertainty. *Management Science*, 68, 3975–4004.
- Bianchi, D., Büchner, M., & Tamoni, A. (2021). Bond risk premiums with machine learning. *Review of Financial Studies*, 34, 1046–1089.
- Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business*, 45, 444–455.
- Black, F., & Litterman, R. (1992). Global portfolio optimization. *Financial Analysts Journal*, 48, 28–43.
- Boons, M. (2016). State variables, macroeconomic activity, and the cross section of individual stocks. *Journal of Financial Economics*, 119, 489–511.

- Boudoukh, J., Michaely, R., Richardson, M., & Roberts, M. R. (2007). On the importance of measuring payout yield: Implications for empirical asset pricing. *Journal of Finance*, 62, 877–915.
- Campbell, J. Y. (1987). Stock returns and the term structure. *Journal of Financial Economics*, 18, 373–399.
- Campbell, J. Y., & Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies*, 1, 195–228.
- Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, 21, 1509–1531.
- Cao, J., Goyal, A., Xiao, X., & Zhan, X. (2023). Implied volatility changes and corporate bond returns. *Management Science*, 69, 1375–1397.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52, 57–82.
- Cederburg, S., O’Doherty, M. S., Wang, F., & Yan, X. S. (2020). On the performance of volatility-managed portfolios. *Journal of Financial Economics*, 138, 95–117.
- Chen, Q., & Choi, J. (2024). Reaching for yield and the cross section of bond returns. *Management Science*, 70, 5226–5245.
- Chung, K. H., Wang, J., & Wu, C. (2019). Volatility and the cross-section of corporate bond returns. *Journal of Financial Economics*, 133, 397–417.
- Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics*, 138, 291–311.
- Cochrane, J. H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance*, 46, 209–237.
- Cochrane, J. H. (2008). The dog that did not bark: A defense of return predictability. *Review of Financial Studies*, 21, 1533–1575.
- Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, 122, 221–247.
- DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial studies*, 22, 1915–1953.
- DeMiguel, V., Martin-Utrera, A., & Uppal, R. (2024). A multifactor perspective on volatility-managed portfolios. *Journal of Finance*, 79, 3859–3891.
- Dickerson, A., Julliard, C., & Mueller, P. (2023). *The corporate bond factor zoo*. (Working Paper)
- Dickerson, A., Mueller, P., & Robotti, C. (2023). Priced risk in corporate bonds. *Journal of Financial Economics*, 150, 103707.
- Dickerson, A., & Nozawa, Y. (2024). *Pricing corporate bonds with credit risk primitives*. (Working Paper)

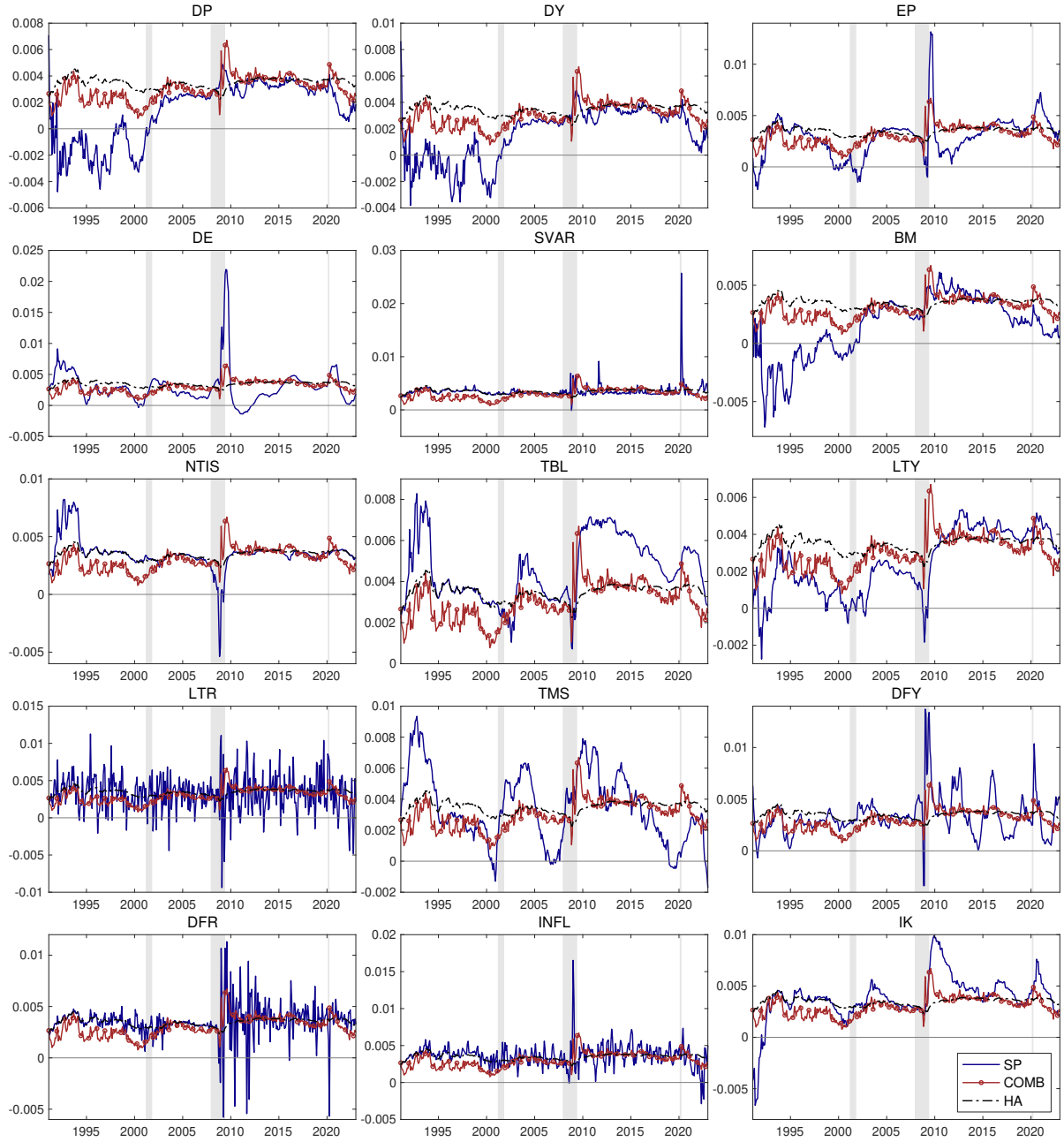
- Dickerson, A., Nozawa, Y., & Robotti, C. (2024). *The low frequency trading arms race: Machines versus delays*. (Working Paper)
- Dickerson, A., Robotti, C., & Rossetti, G. (2023). *Return-based anomalies in corporate bonds: Are they there?* (Working Paper)
- Dick-Nielsen, J., Feldhütter, P., Pedersen, L. H., & Stolborg, C. (2023). *Corporate bond factors: Replication failures and a new framework*. (Working Paper)
- Dick-Nielsen, J., & Rossi, M. (2019). The cost of immediacy for corporate bonds. *Review of Financial Studies*, 32, 1–41.
- Ehsani, S., & Linnainmaa, J. T. (2022). Factor momentum and the momentum factor. *Journal of Finance*, 77, 1877–1919.
- Elkamhi, R., Jo, C., & Nozawa, Y. (2024). A one-factor model of corporate bond premia. *Management Science*, 70, 1875–1900.
- Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, 22, 3–25.
- Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, 25, 23–49.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47, 427–465.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33, 3–56.
- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116, 1–22.
- Farmer, L. E., Schmidt, L., & Timmermann, A. (2023). Pockets of predictability. *Journal of Finance*, 78, 1279–1341.
- Feng, G., He, X., Wang, Y., & Wu, C. (2025). Predicting individual corporate bond returns. *Journal of Banking & Finance*, 171, 107372.
- Ferson, W. E., & Siegel, A. F. (2001). The efficient use of conditioning information in portfolios. *Journal of Finance*, 56, 967–982.
- Ferson, W. E., & Siegel, A. F. (2009). Testing portfolio efficiency with conditioning information. *Review of Financial Studies*, 22, 2735–2758.
- Ferson, W. E., Siegel, A. F., & Wang, J. L. (2019). *Asymptotic variances for tests of portfolio efficiency and factor model comparisons with conditioning information*. (Working Paper)
- Fleming, J., Kirby, C., & Ostdiek, B. (2001). The economic value of volatility timing. *Journal of Finance*, 56, 329–352.
- Fleming, J., Kirby, C., & Ostdiek, B. (2003). The economic value of volatility timing using “realized” volatility. *Journal of Financial Economics*, 67, 473–509.

- Gómez-Cram, R. (2022). Late to recessions: Stocks and the business cycle. *Journal of Finance*, 77, 923–966.
- Greenwood, R., & Hanson, S. G. (2013). Issuer quality and corporate bond returns. *Review of Financial Studies*, 26, 1483–1525.
- Gupta, T., & Kelly, B. (2019). Factor momentum everywhere. *Journal of Portfolio Management*, 45, 13–36.
- Haddad, V., Kozak, S., & Santosh, S. (2020). Factor timing. *Review of Financial Studies*, 33, 1980–2018.
- He, X., Feng, G., Wang, J., & Wu, C. (2022). *Corporate bond pricing via benchmark combination model*. (Working Paper)
- He, Z., Kelly, B., & Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, 126, 1–35.
- Hodrick, R. J. (1992). Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *Review of Financial Studies*, 5, 357–386.
- Hollstein, F., & Prokopczuk, M. (2023). Managing the market portfolio. *Management Science*, 69, 3675–3696.
- Hong, Y., Lin, H., & Wu, C. (2012). Are corporate bond market returns predictable? *Journal of Banking & Finance*, 36, 2216–2232.
- Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *Review of Financial Studies*, 33, 2019–2133.
- Houweling, P., & Van Zundert, J. (2017). Factor investing in the corporate bond market. *Financial Analysts Journal*, 73, 100–115.
- Huang, D., Jiang, F., Tu, J., & Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *Review of Financial Studies*, 28, 791–837.
- Israela, R., Palhares, D., & Richardson, S. (2018). Common factors in corporate bond returns. *Journal of Investment Management*, 16, 17–46.
- Ivashchenko, A., & Kosowski, R. (2024). Transaction costs and capacity of systematic corporate bond strategies. *Financial Analysts Journal*, 80, 53–80.
- Jagannathan, R., & Ma, T. (2003). Risk reduction in large portfolios: Why imposing the wrong constraints helps. *Journal of Finance*, 58, 1651–1683.
- Jiang, F., Xue, B., Yan, H., & Zhan, J. (2024). *Narrative-managed portfolio*. (Working Paper)
- Jobson, J. D., & Korkie, B. M. (1981). Performance hypothesis testing with the Sharpe and Treynor measures. *Journal of Finance*, 36, 889–908.
- Jostova, G., Nikolova, S., Philipov, A., & Stahel, C. W. (2013). Momentum in corporate bond returns. *Review of Financial Studies*, 26, 1649–1693.
- Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105, 1177–1216.

- Karakaya, M. M. (2014). *Characteristics and expected returns in individual equity options*. (Working Paper)
- Keim, D. B., & Stambaugh, R. F. (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics*, *17*, 357–390.
- Kelly, B., Palhares, D., & Pruitt, S. (2023). Modeling corporate bond returns. *Journal of Finance*, *78*, 1967–2008.
- Kelly, B. T., & Pruitt, S. (2022). *Reconciling trace bond returns*. (Working Paper)
- Lettau, M., & Ludvigson, S. (2001). Consumption, aggregate wealth, and expected stock returns. *Journal of Finance*, *56*, 815–849.
- Lin, H., Wang, J., & Wu, C. (2014). Predictions of corporate bond excess returns. *Journal of Financial Markets*, *21*, 123–152.
- Lin, H., Wu, C., & Zhou, G. (2018). Forecasting corporate bond returns with a large set of predictors: An iterated combination approach. *Management Science*, *64*, 4218–4238.
- Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, *47*, 13–37.
- Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *Journal of Finance*, *77*, 1133–1177.
- Ludvigson, S. C., Ma, S., & Ng, S. (2021). Uncertainty and business cycles: Exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics*, *13*, 369–410.
- Lustig, H., Roussanov, N., & Verdelhan, A. (2011). Common risk factors in currency markets. *Review of Financial Studies*, *24*, 3731–3777.
- Maio, P., & Santa-Clara, P. (2017). Short-term interest rates and stock market anomalies. *Journal of Financial and Quantitative Analysis*, *52*, 927–961.
- Marquering, W., & Verbeek, M. (2004). The economic value of predicting stock index returns and volatility. *Journal of Financial and Quantitative Analysis*, *39*, 407–429.
- Maurer, T. A., Tô, T.-D., & Tran, N.-K. (2023). Market timing and predictability in fx markets. *Review of Finance*, *27*, 223–246.
- Moreira, A., & Muir, T. (2017). Volatility-managed portfolios. *Journal of Finance*, *72*, 1611–1644.
- Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science*, *60*, 1772–1791.
- Newey, W. K., & West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica*, *55*, 703–708.
- Nozawa, Y., Qiu, Y., & Xiong, Y. (2024). *Disagreement and bond PEAD*. (Working Paper)
- Pástor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*, 642–685.

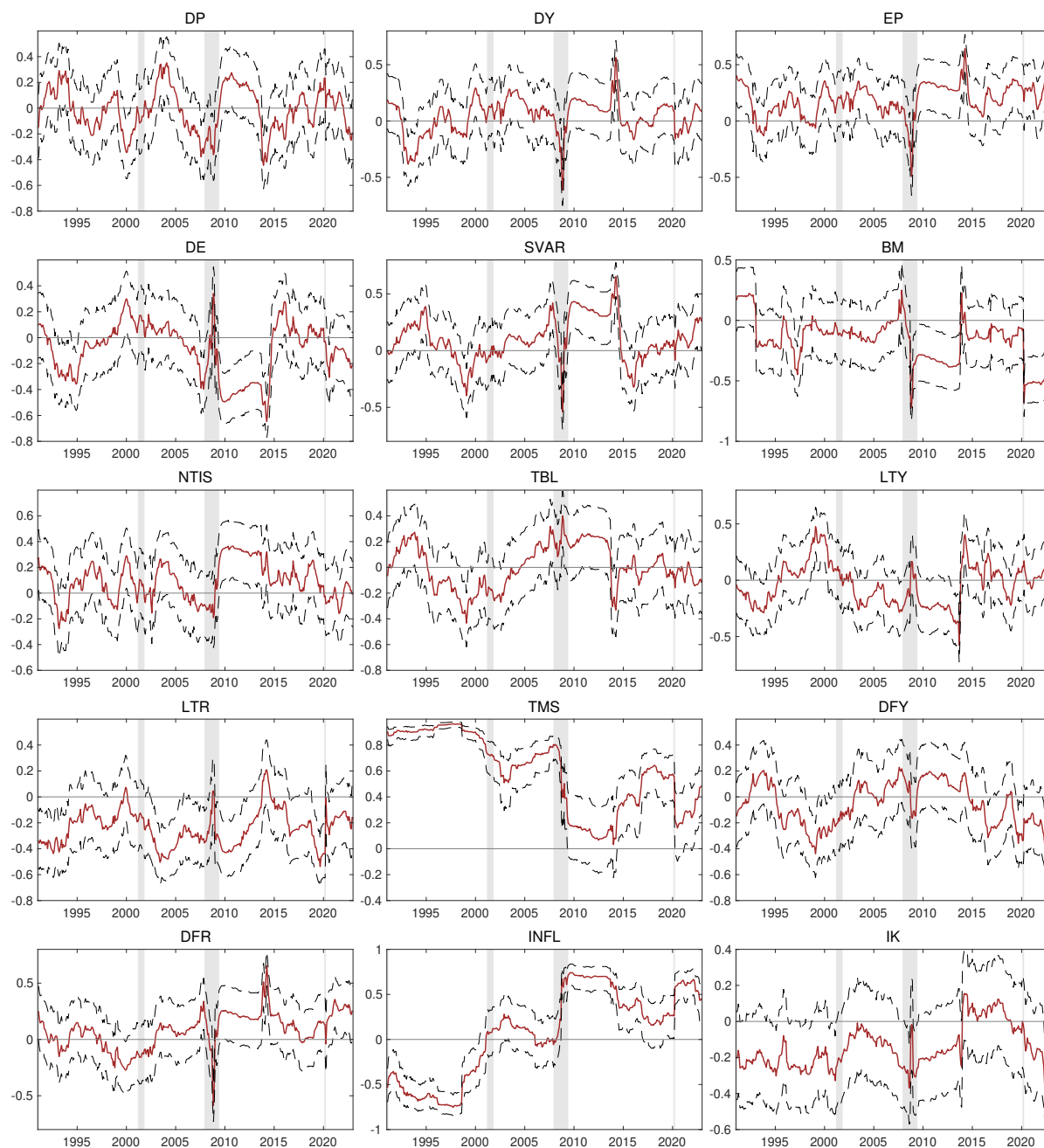
- Paye, B. S., & Timmermann, A. (2006). Instability of return prediction models. *Journal of Empirical Finance*, 13, 274–315.
- Peñaranda, F. (2016). Understanding portfolio efficiency with conditioning information. *Journal of Financial and Quantitative Analysis*, 51, 985–1011.
- Petkova, R. (2006). Do the fama–french factors proxy for innovations in predictive variables? *Journal of Finance*, 61, 581–612.
- Rapach, D., & Zhou, G. (2013). Forecasting stock returns. In *Handbook of economic forecasting* (Vol. 2, pp. 328–383). Elsevier.
- Rapach, D. E., Ringgenberg, M. C., & Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, 121, 46–65.
- Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies*, 23, 821–862.
- Rapach, D. E., & Wohar, M. E. (2006). Structural breaks and predictive regression models of aggregate US stock returns. *Journal of Financial Econometrics*, 4, 238–274.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, 19, 425–442.
- Stock, J. H., & Watson, M. W. (1998). A comparison of linear and nonlinear univariate models for forecasting macroeconomic time series. In R. F. Engle & H. White (Eds.), *Cointegration, Causality, and Forecasting: A Festschrift in Honour of Clive Granger* (p. 1-44). Oxford University Press.
- Stock, J. H., & Watson, M. W. (2004). Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting*, 23, 405–430.
- Thornton, D. L., & Valente, G. (2012). Out-of-sample predictions of bond excess returns and forward rates: An asset allocation perspective. *Review of Financial Studies*, 25, 3141–3168.
- van Binsbergen, J. H., Nozawa, Y., & Schwert, M. (2023). Duration-based valuation of corporate bonds. *Review of Financial Studies*, forthcoming.
- Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, 21, 1455–1508.

Figure 1: **Out-of-sample corporate bond market return forecasts**



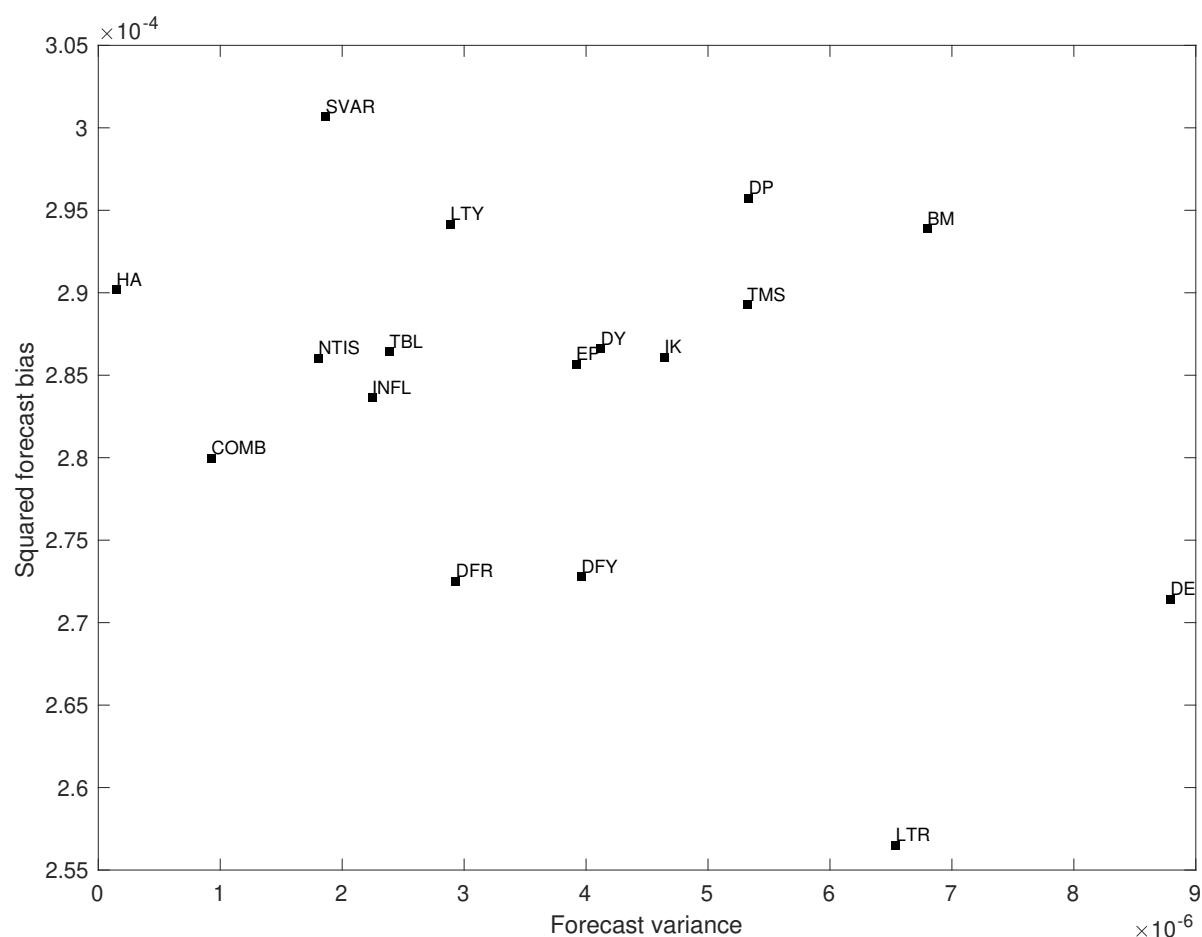
Notes: This figure plots the time series of the monthly out-of-sample corporate bond market return forecasts. SP corresponds to results from individual predictive regression models using 15 single predictors of the form: $r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1}$, where r_{t+1} is the excess returns of the corporate bond market portfolio at time $t + 1$, and $x_{i,t}$ is the predictor i at time t whose predictive power is of interest. COMB is the mean combination forecast, which is the equally weighted average of the one-month-ahead return forecasts derived from individual predictors. HA denotes the historical average. The shaded areas correspond to the NBER recession periods. The out-of-sample period is from February 1991 to December 2022.

Figure 2: Correlations between corporate bond market returns and individual predictors



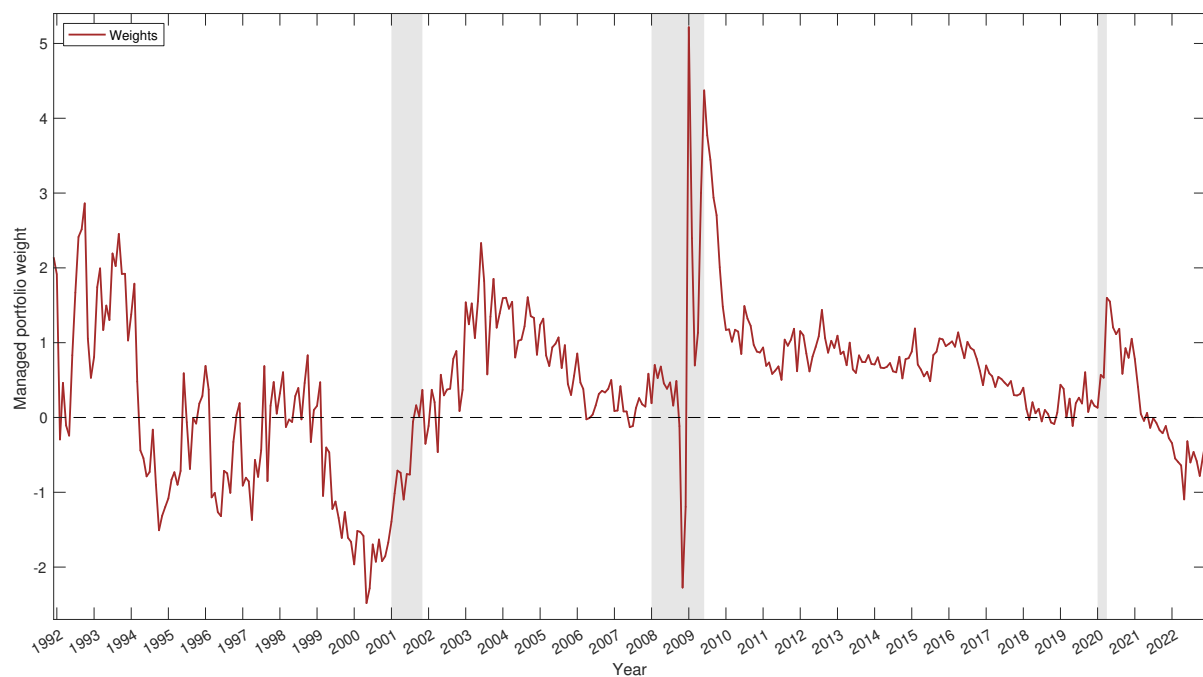
Notes: This figure plots the time-varying correlations between corporate bond market returns and individual predictors based on 5-year rolling windows. The solid lines represent the correlations estimated at the end date of the 5-year period. The dashed lines indicate the 95% confidence intervals. The shaded areas correspond to the NBER recession periods. The sample period is from January 1986 to December 2022.

Figure 3: **Forecast variance and squared forecast bias**



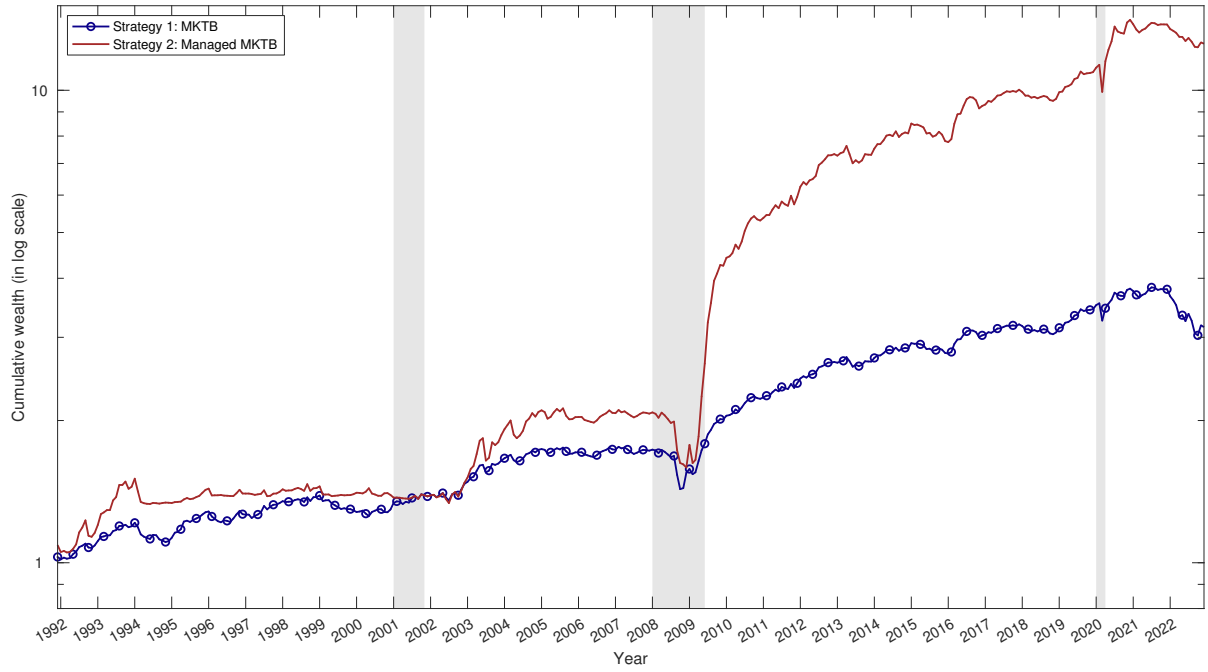
Notes: This figure plots the forecast variance (the vertical axis) against the squared forecast bias (the horizontal axis) of the out-of-sample corporate bond market return forecasts. The COMB corresponds to the mean combination forecast, which is the equally weighted average of the one-month-ahead return forecasts derived from individual predictors. The HA indicates the historical average forecast. The other points correspond to return forecasts based on predictive regression models using individual predictors. The out-of-sample period is from February 1991 to December 2022.

Figure 4: **Timing weights in the managed corporate bond market portfolio**



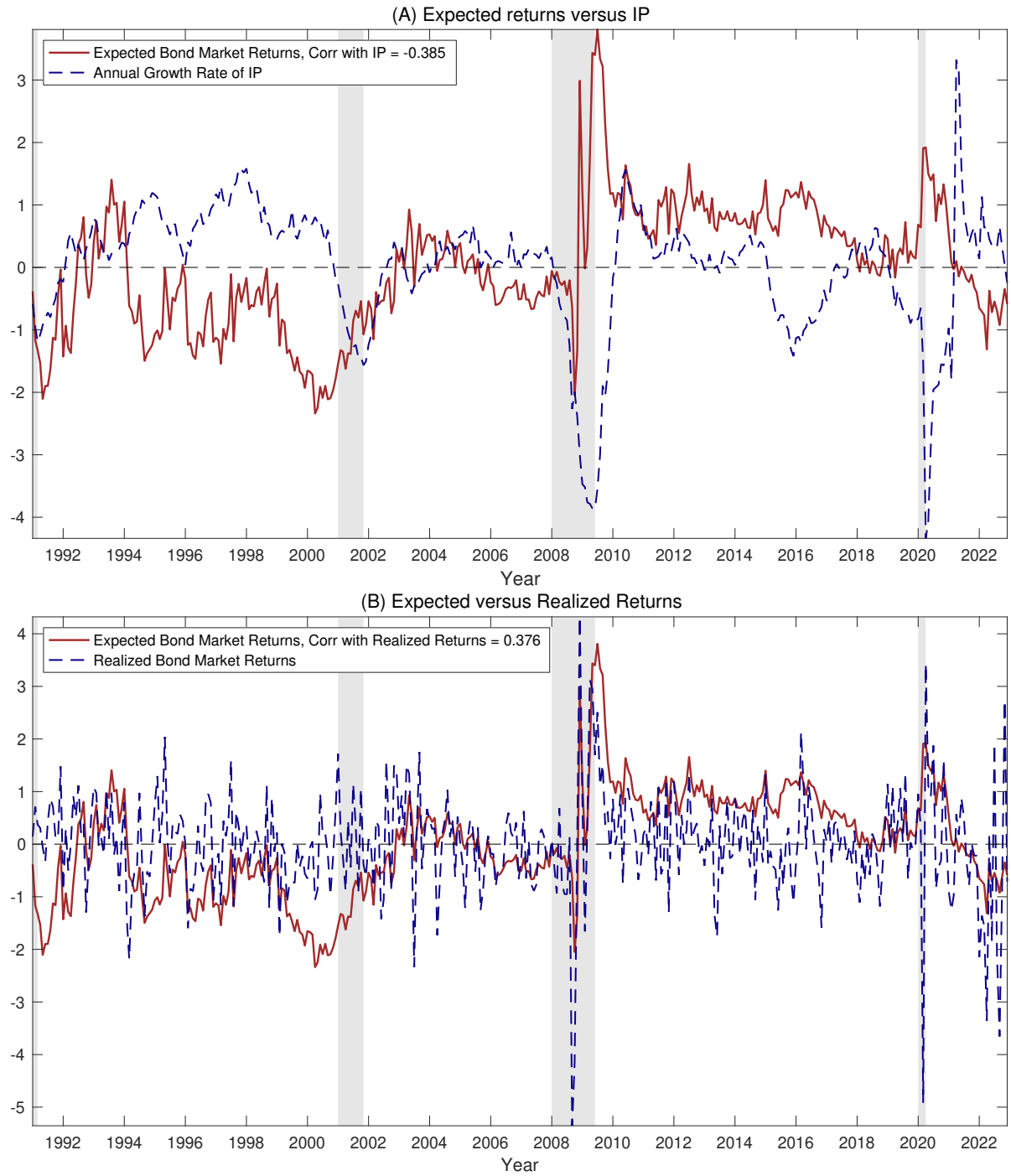
Notes: This figure plots the time series of the weights in the managed corporate bond market portfolio implied by the timing strategy. The weights in the managed portfolio are proportional to the corporate bond market return forecasts derived from the mean forecast combination. We conditionally demean the return forecasts and scale the weights in the managed market portfolio to match its conditional standard deviation with that of the corporate bond market portfolio using information available at time t . Thus, the time-series average of investment in the managed market portfolio implied by the timing strategy is approximately zero. The shaded areas correspond to the NBER recession periods. The sample period is from December 1991 to December 2022.

Figure 5: Cumulative returns of corporate bond market timing strategy



Notes: This figure plots the cumulative returns of a plain corporate bond market strategy (MKTB, financed with the one-month risk-free assets) and a strategy augmented with the combination forecast-managed market portfolio (Managed MKTB), i.e., we combine the plain corporate bond market portfolio with a conditionally demeaned investment in which the weights are implied by the out-of-sample market return combination forecasts. By doing so, two strategies invest approximately 100% in the corporate bond market portfolio on average over time. We assume that both strategies start with an initial investment of one unit dollar in December 1991. The vertical axis is in the logarithm scale. The shaded areas correspond to the NBER recession periods. The sample period is from December 1991 to December 2022.

Figure 6: **Expected corporate bond market returns and economic growth**



Notes: In this figure, we compare the expected corporate bond market returns with economic growth and realized bond market returns. The expected bond market returns are obtained from the mean-combination forecast method. Panel A plots the time-series of expected bond market returns (solid line) against the annual growth rate of industrial production (IP) in the US (dashed line). Panel B shows the dynamics of expected bond market returns (solid line) and realized returns (dashed line). All series are standardized with zero mean and unit variance for ease of comparison. The shaded areas correspond to the NBER recession periods. The sample period is from February 1991 to December 2022.

Table 1: Summary statistics

	Mean	SD	Skew	Kurt	$\rho(1)$	Min	10th	Med	90th	Max	
<i>Panel A: Predictors</i>											
DP	-3.88	0.30	0.21	2.30	0.99	-4.52	-4.28	-3.93	-3.42	-3.24	
DY	-3.87	0.30	0.19	2.32	0.99	-4.53	-4.28	-3.93	-3.41	-3.23	
EP	-3.08	0.35	-1.82	9.35	0.98	-4.84	-3.45	-3.05	-2.73	-2.46	
DE	-0.80	0.37	2.82	15.15	0.98	-1.24	-1.15	-0.88	-0.47	1.38	
SVAR	0.00	0.01	8.28	83.93	0.38	0.00	0.00	0.00	0.01	0.07	
BM	0.30	0.10	0.37	2.60	0.98	0.12	0.18	0.30	0.44	0.58	
NTIS	0.00	0.02	-0.18	2.85	0.98	-0.06	-0.02	0.01	0.03	0.05	
TBL	0.03	0.02	0.30	1.85	1.00	0.00	0.00	0.03	0.06	0.09	
LTY	0.05	0.02	0.09	2.01	0.99	0.01	0.02	0.05	0.08	0.10	
LTR	0.01	0.03	0.12	4.68	0.08	-0.11	-0.03	0.01	0.04	0.14	
TMS	0.02	0.01	0.00	1.92	0.97	-0.01	0.00	0.02	0.04	0.05	
DFY	0.01	0.00	2.99	17.04	0.96	0.01	0.01	0.01	0.01	0.03	
DFR	0.00	0.02	-0.82	10.52	0.02	-0.10	-0.01	0.00	0.02	0.07	
INFL	0.00	0.00	-0.61	7.52	0.50	-0.02	0.00	0.00	0.01	0.01	
IK	0.14	0.01	-0.03	3.01	0.98	0.12	0.13	0.14	0.16	0.17	
<i>Panel B: Corporate bond risk factors</i>											
	Mean	<i>t</i> -stat	SD	Skew	Kurt	$\rho(1)$	Min	10th	Med	90th	Max
MKTB	0.32	3.61	1.70	-0.49	7.77	0.18	-0.09	-0.01	0.00	0.02	0.08
CRY	0.34	2.58	2.38	-0.13	13.95	0.20	-0.16	-0.02	0.00	0.02	0.14
DEF	0.03	0.39	1.68	-0.82	10.52	0.02	-0.10	-0.01	0.00	0.02	0.07
DUR	0.19	1.82	2.24	-0.67	7.44	0.01	-0.13	-0.02	0.00	0.03	0.08
LTR	0.11	2.10	1.00	0.16	11.74	0.06	-0.06	-0.01	0.00	0.01	0.06
MOMB	-0.07	-0.60	2.16	-0.48	9.70	0.08	-0.11	-0.02	0.00	0.02	0.10
PEADB	0.13	6.32	0.46	1.61	17.02	0.03	-0.02	0.00	0.00	0.01	0.04
STR	0.07	0.83	1.74	1.15	11.22	0.00	-0.07	-0.02	0.00	0.02	0.13
TERM	0.36	2.51	3.00	0.16	4.70	0.07	-0.11	-0.03	0.00	0.04	0.14
VAL	0.21	2.41	1.62	-0.24	11.78	0.14	-0.10	-0.01	0.00	0.02	0.08
<i>Panel C: Equity risk factors</i>											
	Mean	<i>t</i> -stat	SD	Skew	Kurt	$\rho(1)$	Min	10th	Med	90th	Max
MKTS	0.69	3.20	4.56	-0.78	5.24	0.03	-0.23	-0.05	0.01	0.06	0.14
SMB	0.06	0.45	2.98	0.39	7.27	-0.01	-0.15	-0.03	0.00	0.03	0.18
HML	0.18	1.05	3.15	0.23	5.52	0.17	-0.14	-0.03	0.00	0.04	0.13
MOMS	0.51	2.33	4.52	-1.46	13.79	0.05	-0.34	-0.05	0.01	0.05	0.18
HKM	0.99	2.92	6.72	-0.45	5.35	0.10	-0.28	-0.07	0.02	0.09	0.31
LIQ	0.29	1.52	3.70	-0.26	4.11	0.06	-0.13	-0.04	0.00	0.05	0.12
RMW	0.38	2.96	2.52	-0.37	13.46	0.15	-0.19	-0.02	0.00	0.03	0.13
CMA	0.29	2.56	2.11	0.48	4.66	0.13	-0.07	-0.02	0.00	0.03	0.09

Notes: This table presents summary statistics for the 15 predictive variables from [Welch & Goyal \(2008\)](#) (Panel A), corporate bond risk factors (Panel B), and equity risk factors (Panel C) over the sample period spanning from January 1986 to December 2022. We report the mean, standard deviation (SD), the [Newey & West \(1986\)](#) adjusted t -statistics (t -stat), skewness (Skew), kurtosis (Kurt), the first order autocorrelation coefficient ($\rho(1)$), minimum (Min), 10th percentile (10th), median (Med), 90th percentile (90th), and maximum (Max) for each variable and factor. Detailed definitions of the variables and factors are provided in [Appendix A](#) and [Appendix B](#), respectively.

Table 2: Return predictability

	$\beta(\%)$	NW t -stat	Hodrick t -stat	$R^2_{IS}(\%)$	$R^2_{OOS}(\%)$	MSPE-adjusted	Δ CER
Panel A: Single predictors							
DP	0.336	3.272***	3.698*** (0.00)	3.853*** <0.00>	-0.783 <0.57>	1.737** [0.04]	-0.064
DY	0.344	3.268***	3.886*** (0.00)	4.045*** <0.00>	-0.096* <0.09>	1.868** [0.03]	0.192
EP	-0.212	-1.336	-1.884** (0.04)	1.542** <0.02>	-0.723 <0.48>	0.414 [0.34]	-2.044
DE	0.396	3.521***	3.608*** (0.00)	5.343*** <0.00>	3.711*** <0.00>	2.465*** [0.01]	-1.493
SVAR	0.349	2.592***	2.219** (0.05)	4.169*** <0.00>	2.099*** <0.00>	1.122 [0.13]	-2.110
BM	0.374	4.067***	4.861*** (0.00)	4.785*** <0.00>	-0.689 <0.44>	1.883** [0.03]	1.767
NTIS	0.013	0.089	0.102 (0.46)	0.005 <0.89>	-1.067 <0.69>	-0.518 [0.70]	0.957
TBL	-0.095	-1.028	-1.223 (0.12)	0.305 <0.28>	-0.668 <0.29>	0.347 [0.36]	-0.095
LTY	0.056	0.591	0.643 (0.26)	0.105 <0.56>	-2.018 <0.93>	-0.752 [0.77]	-1.347
LTR	0.292	2.506**	2.351*** (0.01)	2.906*** <0.00>	2.007*** <0.00>	1.961** [0.02]	0.570
TMS	0.230	2.434**	2.559*** (0.01)	1.813** <0.01>	1.337*** <0.00>	2.275** [0.01]	1.309
DFY	0.388	2.947***	2.637** (0.01)	5.137*** <0.00>	2.411*** <0.00>	2.061** [0.02]	-0.891
DFR	0.041	0.264	0.231 (0.41)	0.058 <0.63>	-2.137 <0.99>	-0.685 [0.75]	-0.327
INFL	-0.199	-2.241**	-1.800** (0.04)	1.359** <0.03>	0.351** <0.04>	0.945 [0.17]	0.064
IK	-0.292	-3.144***	-3.738*** (0.00)	2.914*** <0.00>	-0.152* <0.09>	1.310* [0.10]	0.480
Panel B: Forecast combination							
COMB	—	—	—	—	1.641*** <0.00>	3.153*** [0.00]	1.267

Notes: This table presents the results of the return predictability analysis. In Panel A, we summarize the in-sample estimation results for the individual predictive regression models. We report the estimated slope coefficient (β), [Newey & West \(1986\)](#) adjusted t -statistics (NW t -stat), [Hodrick \(1992\)](#) t -statistics (Hodrick t -stat) with their bootstrapped p values for slope estimates (in parentheses), and R^2_{IS} statistics of univariate predictive regression of the form: $r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1}$, where r_{t+1} is the excess returns of the corporate bond market portfolio at time $t + 1$, and $x_{i,t}$ is the predictor i at time t whose predictive power is of interest. Next, we report the out-of-sample prediction results, including both statistical and economic evaluations. We use the out-of-sample R^2 (R^2_{OOS}) of [Campbell & Thompson \(2008\)](#), the MSPE-adjusted statistic of [Clark & West \(2007\)](#) with the standard normal distribution to obtain the one-sided (upper-tail) p -value of the null hypothesis (in square brackets), and annualized certainty equivalent gains (Δ CER). We evaluate the statistical significance of both in- and out-of-sample R^2 by using the bootstrap approach of [Welch & Goyal \(2008\)](#) and report the corresponding p -values in angle brackets. Each predictor variable is standardized to have a standard deviation of one and a mean of zero. In Panel B, we present the out-of-sample forecasting results for the mean combination forecast, which is the equally weighted average of the one-month-ahead return forecasts derived from individual predictors. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The out-of-sample period is from February 1991 to December 2022.

Table 3: Performance of managed corporate bond market portfolio

Panel A: The combination forecast-managed corporate bond market portfolio											
Average return	Return										
	4.932**										
	(2.48)										
Panel B: Cross-sectional evaluation											
CAPMB	Alpha	MKTB									
	2.942**	0.513**									
	(2.22)	(2.44)									
PEADB	Alpha	PEADB									
	6.370***	-0.811**									
	(2.80)	(-2.11)									
BOND2	Alpha	MKTB	PEADB								
	3.858**	0.486**	-0.459								
	(2.56)	(2.33)	(-1.28)								
MKT2	Alpha	MKTB	MKTS								
	4.180**	0.055	0.023								
	(2.56)	(0.94)	(0.46)								
HKM	Alpha	MKTS	HKM								
	2.988**	0.527**	-0.012								
	(2.23)	(2.45)	(-0.51)								
FF2	Alpha	DEF	TERM								
	4.084***	0.499*	0.146								
	(2.64)	(1.88)	(1.08)								
BOND5	Alpha	MKTB	PEADB	LTR	MOMB	STR					
	3.294**	0.549***	-0.485	0.422	0.177*	-0.089					
	(2.08)	(2.71)	(-1.38)	(1.38)	(1.89)	(-0.60)					
IPR5	Alpha	CRY	DUR	MOMB	VAL	MOMS					
	3.005**	0.742***	-0.068	0.373***	-0.291	-0.021					
	(2.13)	(4.00)	(-0.73)	(3.92)	(-1.47)	(-0.67)					
STOCK5	Alpha	MKTS	SMB	HML	MOMS	LIQ					
	4.520**	0.059	-0.033	0.031	-0.068	0.067					
	(2.37)	(1.47)	(-0.88)	(0.77)	(-1.43)	(1.50)					
FF5	Alpha	DEF	TERM	MKTS	SMB	HML					
	3.980**	0.489*	0.141	0.016	-0.042	0.025					
	(2.50)	(1.78)	(0.98)	(0.47)	(-1.01)	(0.58)					
BS6	Alpha	MKTB	MKTS	SMB	HML	MOMS	LIQ				
	3.229**	0.503**	-0.026	-0.019	0.028	-0.052	0.055				
	(2.19)	(2.39)	(-0.86)	(-0.48)	(0.82)	(-1.32)	(1.21)				
STOCK6	Alpha	MKTS	SMB	HML	MOMS	RMW	CMA				
	4.314**	0.082*	-0.027	-0.034	-0.070	0.009	0.119				
	(2.24)	(1.85)	(-0.68)	(-0.56)	(-1.51)	(0.15)	(1.42)				
BS7	Alpha	MKTB	MKTS	SMB	HML	MOMS	RMW	CMA			
	3.129**	0.518**	-0.011	-0.028	-0.028	-0.054	-0.030	0.127*			
	(2.01)	(2.47)	(-0.29)	(-0.75)	(-0.53)	(-1.38)	(-0.50)	(1.66)			
BS10	Alpha	MKTB	PEADB	DEF	LTR	MOMB	STR	TERM	MKTS	SMB	HML
	3.861**	1.078***	-0.344	-0.140	0.366*	0.275***	-0.127	-0.376**	-0.091**	-0.081**	-0.053
	(2.09)	(3.73)	(-0.89)	(-0.62)	(1.72)	(2.94)	(-0.94)	(-2.17)	(-2.29)	(-2.02)	(-1.30)

Notes: This table presents the monthly performance of the managed corporate bond market portfolio. We calculate the annualized average returns, multifactor alphas, and factor exposures of the managed corporate bond market portfolio. The weights in the managed portfolio are proportional to the out-of-sample corporate bond market return forecasts derived from the mean forecast combination. We conditionally demean the return forecasts and scale the weights in the managed market portfolio to match its conditional standard deviation with that of the corporate bond market portfolio using information available at time t . Thus, the time-series average of investment in the managed market portfolio implied by the timing strategy is approximately zero. The alphas and factor exposures are obtained from estimating the regression in Equation (7). Detailed definitions of the factor models are provided in Section 4.2. The Newey & West (1986) adjusted t -statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from December 1991 to December 2022.

Table 4: Performance of enhanced strategies

	CAPMB	PEADB	BOND2	MKT2	HKM	FF2	BOND5	IPR5	STOCK5	FF5	BS6	STOCK6	BS7	BS10
Panel A: Full-sample Sharpe ratio														
SR	0.648	1.049	1.370	0.584	0.709	0.510	1.472	0.756	0.913	0.838	1.034	1.284	1.355	1.691
SR^*	0.764	1.331	1.470	0.793	0.820	0.750	1.546	0.878	1.087	0.995	1.127	1.402	1.424	1.789
ΔSR	0.116	0.283	0.100	0.210	0.111	0.240	0.074	0.122	0.174	0.157	0.094	0.118	0.069	0.098
ω^*	0.412	0.130	0.078	0.711	0.429	0.530	0.058	0.459	0.344	0.427	0.239	0.186	0.143	0.068
Panel B: Out-of-sample strategy – Cederburg et al. (2020)’s approach														
SR_{OOS}	0.567	0.898	1.192	0.295	0.577	0.352	1.112	0.371	0.466	0.518	0.581	0.936	0.971	1.124
SR_{OOS}^*	0.673	1.246	1.306	0.551	0.681	0.637	1.200	0.541	0.671	0.694	0.680	1.038	1.025	1.253
ΔSR_{OOS}	0.106**	0.348***	0.114**	0.256***	0.104**	0.285***	0.089**	0.169**	0.206***	0.176***	0.099**	0.103**	0.053*	0.129**
p -value	(0.021)	(0.000)	(0.025)	(0.004)	(0.021)	(0.002)	(0.042)	(0.023)	(0.003)	(0.009)	(0.025)	(0.039)	(0.080)	(0.014)
Utility (%)	1.915	2.480	0.935	4.684	1.998	4.840	0.864	3.185	5.282	3.958	2.125	0.979	0.664	1.016
ω_{OOS}^*	0.156	0.085	0.035	0.675	0.166	0.359	0.028	0.284	0.212	0.197	0.105	0.108	0.050	0.039
Panel C: Out-of-sample strategy – Optimal tangency portfolio														
SR_{OOS}	0.625	0.898	1.192	0.292	0.611	-0.004	1.089	0.345	0.506	0.378	0.583	0.952	0.990	1.009
SR_{OOS}^*	0.740	1.243	1.301	0.500	0.726	0.454	1.171	0.562	0.675	0.525	0.671	1.052	1.043	1.146
ΔSR_{OOS}	0.114**	0.345***	0.109**	0.208*	0.115**	0.458**	0.083*	0.217*	0.169**	0.147**	0.088*	0.101*	0.053*	0.137**
p -value	(0.040)	(0.000)	(0.031)	(0.087)	(0.039)	(0.037)	(0.060)	(0.050)	(0.023)	(0.013)	(0.052)	(0.053)	(0.096)	(0.012)
Utility (%)	0.496	0.492	0.190	1.973	0.496	4.338	0.199	1.833	0.561	1.210	0.371	0.099	0.131	0.291
ω_{OOS}^*	0.156	0.085	0.035	0.675	0.166	0.359	0.028	0.284	0.212	0.197	0.105	0.108	0.050	0.039
Panel D: The 1/N approach														
$SR_{1/N}$	0.648	1.049	0.962	0.583	0.655	0.509	0.763	0.616	0.809	0.722	0.893	1.030	1.129	0.856
$SR_{1/N}^*$	0.759	0.863	0.932	0.680	0.778	0.725	0.873	0.738	0.936	0.833	0.993	1.168	1.231	0.931
$\Delta SR_{1/N}$	0.111	-0.186	-0.029	0.097***	0.123*	0.216*	0.111	0.122**	0.127**	0.111**	0.100**	0.138**	0.102*	0.075*
p -value	(0.360)	(0.463)	(0.821)	(0.009)	(0.054)	(0.053)	(0.274)	(0.026)	(0.011)	(0.036)	(0.031)	(0.014)	(0.052)	(0.089)
Utility (%)	0.535	1.528	0.678	-1.186	-0.273	0.870	0.563	0.359	0.099	0.247	0.091	0.089	0.082	0.219
$\omega_{1/N}^*$	0.500	0.500	0.333	0.333	0.333	0.333	0.167	0.167	0.167	0.167	0.143	0.143	0.125	0.091

Notes: This table summarizes the performance of the enhanced strategies. We compare the optimal portfolios of the space spanned by factors of pricing models alone with the optimal combination portfolios in which the model space is augmented by the managed corporate bond market portfolio. Panel A reports the full-sample gains in annualized Sharpe ratios in the optimal combination portfolios based on fourteen factor models. SR is the annualized in-sample Sharpe ratio of the optimal combination portfolio implied by a factor model, SR^* is the annualized in-sample Sharpe ratio of the model expanded by the managed bond market portfolio, and ΔSR denotes the difference in Sharpe ratios. ω^* represents the optimal relative weights on the managed bond market portfolio in the optimal combination portfolios. Panels B and C present the results for the out-of-sample combination strategy based on the Cederburg et al. (2020)’s approach and the optimal tangency portfolio, respectively. The optimal investment weights are estimated by using the data available up to time t . We use the subscript OOS to denote the statistics of out-of-sample approaches. To test whether the Sharpe ratio difference is statistically significant, we use the Jobson & Korkie (1981) test with a null hypothesis $H_0 : \Delta SR = 0$ and report the corresponding p -values in parentheses. Utility is the relative utility gain of the optimal combination strategy relative to strategies without the managed market portfolio for investors. In Panel D, we consider a naive 1/N approach, i.e., to weigh all considered factors and managed bond market portfolio equally, and indicate corresponding statistics by using a subscript 1/N. Detailed definitions of the factor models are provided in Section 4.2. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from December 1991 to December 2022.

Table 5: Managed by single predictors' past realizations

	Return	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}
DP	0.134 (0.11)	1.621 (1.53)	-0.224 (-0.16)	1.763 (1.07)	0.488 (0.43)	1.536 (1.46)	1.304 (1.32)	0.558 (0.39)	1.332 (1.37)	1.306 (1.05)	1.775* (1.82)	2.485** (2.10)	0.649 (0.50)	1.824 (1.52)	0.716 (0.53)
DY	0.143 (0.12)	1.759* (1.73)	-0.377 (-0.25)	1.761 (1.13)	0.554 (0.48)	1.705* (1.69)	1.386 (1.40)	0.560 (0.44)	1.422 (1.47)	1.497 (1.15)	1.935** (1.98)	2.745** (2.31)	0.805 (0.59)	2.046* (1.70)	0.783 (0.65)
EP	-2.812 (-1.42)	-0.036 (-0.03)	-4.173 (-1.36)	-0.576 (-0.30)	-1.781 (-1.17)	-0.112 (-0.10)	-1.290 (-0.83)	0.806 (0.57)	-1.349 (-0.86)	-2.984 (-1.31)	-0.984 (-0.67)	-1.048 (-0.62)	-3.114 (-1.46)	-1.220 (-0.76)	0.581 (0.41)
DE	1.841 (0.80)	0.531 (0.34)	2.282 (0.65)	0.552 (0.19)	1.197 (0.64)	0.492 (0.31)	1.395 (0.77)	-2.152 (-0.94)	1.309 (0.63)	2.816 (1.06)	1.586 (0.95)	2.003 (0.92)	2.092 (0.80)	1.341 (0.61)	-1.748 (-0.80)
SVAR	4.786 (1.41)	1.798 (0.56)	5.234 (1.08)	1.196 (0.25)	4.562 (1.08)	2.158 (0.59)	3.080 (0.94)	0.662 (0.13)	3.933 (1.22)	5.269 (1.17)	3.100 (0.76)	2.963 (0.77)	6.351 (1.13)	4.053 (0.84)	0.901 (0.16)
BM	0.710 (0.71)	2.207*** (2.80)	0.408 (0.32)	2.419** (2.22)	1.121 (1.18)	2.165*** (2.76)	1.787** (2.11)	1.420* (1.66)	1.681** (2.09)	1.819* (1.76)	2.263*** (2.70)	2.949*** (3.29)	1.404 (1.29)	2.526*** (2.78)	1.653** (1.96)
NTIS	0.864 (0.62)	2.362 (1.26)	1.410 (0.67)	3.562 (1.29)	1.397 (0.90)	2.405 (1.27)	1.877 (1.24)	5.003* (1.81)	2.239 (1.23)	0.770 (0.45)	1.564 (1.01)	1.720 (0.86)	1.353 (0.79)	2.304 (1.12)	4.435* (1.70)
TBL	-4.687*** (-3.15)	-1.136 (-1.31)	-5.550*** (-2.77)	-0.805 (-0.73)	-3.578** (-2.51)	-1.224 (-1.38)	-2.334** (-2.12)	0.180 (0.18)	-2.216** (-2.16)	-3.913** (-2.51)	-1.885 (-1.62)	-1.379 (-1.42)	-4.011** (-2.54)	-1.503 (-1.44)	-0.098 (-0.09)
LTY	-4.348*** (-3.00)	0.019 (0.03)	-6.147*** (-2.91)	-0.433 (-0.59)	-2.807** (-2.04)	0.055 (0.08)	-1.440 (-1.53)	0.083 (0.11)	-1.117 (-1.38)	-2.960** (-1.96)	-0.728 (-0.72)	0.058 (0.08)	-2.915** (-1.98)	0.070 (0.09)	-0.166 (-0.22)
LTR	2.985** (1.98)	2.127* (1.96)	2.688** (2.43)	1.457 (0.83)	3.022* (1.86)	2.251* (1.90)	2.212** (2.26)	0.464 (0.19)	3.011* (1.89)	3.206 (1.54)	2.523** (2.04)	2.510* (1.69)	3.112 (1.58)	2.464* (1.69)	0.995 (0.51)
TMS	2.389* (1.83)	2.216* (1.65)	0.994 (0.53)	0.523 (0.33)	2.612** (1.99)	2.459* (1.77)	2.239* (1.81)	-0.598 (-0.43)	2.839** (2.21)	3.072** (2.02)	2.443* (1.77)	2.785* (1.71)	3.471** (2.31)	3.177** (2.01)	-0.461 (-0.31)
DFY	1.480 (0.84)	-0.310 (-0.19)	0.665 (0.28)	-1.935 (-0.65)	0.994 (0.57)	-0.262 (-0.16)	0.270 (0.19)	-4.473 (-1.51)	0.388 (0.23)	2.370 (1.11)	0.759 (0.51)	1.129 (0.60)	1.721 (0.83)	0.534 (0.28)	-3.722 (-1.31)
DFR	1.238 (0.63)	2.970 (0.96)	1.468 (0.39)	3.890 (0.75)	2.578 (0.92)	3.427 (1.04)	1.928 (0.79)	3.496 (0.73)	1.388 (0.63)	2.767 (0.95)	3.286 (0.98)	3.498 (1.02)	2.522 (0.90)	3.303 (0.98)	4.937 (0.93)
INFL	-2.931** (-2.35)	-2.218* (-1.92)	-1.468 (-1.20)	-0.244 (-0.12)	-2.952** (-2.28)	-2.326* (-1.95)	-2.224** (-2.07)	0.260 (0.11)	-3.001** (-2.20)	-3.017* (-1.93)	-2.301* (-1.80)	-2.382* (-1.78)	-3.026** (-2.00)	-2.434* (-1.87)	0.142 (0.06)
IK	-3.597*** (-2.91)	-2.378*** (-2.58)	-4.449*** (-3.13)	-2.913*** (-2.72)	-3.237*** (-2.94)	-2.472*** (-2.64)	-2.815*** (-2.82)	-2.399** (-2.04)	-2.846*** (-2.83)	-3.640*** (-2.87)	-2.733*** (-2.72)	-2.753*** (-2.62)	-3.670*** (-2.74)	-2.786** (-2.46)	-2.674** (-2.17)

Notes: This table presents the monthly performance of the managed corporate bond market portfolio that uses single predictors' past realizations as conditioning variables. We calculate the annualized average returns and multifactor alphas of the managed corporate bond market portfolio. The weights in the managed portfolio are proportional to the out-of-sample corporate bond market return forecasts based on single predictors' past realizations. We conditionally demean the return forecasts and scale the weights in the managed market portfolio to match its conditional standard deviation with that of the corporate bond market portfolio using information available at time t . The alphas are obtained from estimating the regression in Equation (7). Detailed definitions of the factor models are provided in Section 4.2. The Newey & West (1986) adjusted t -statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from December 1991 to December 2022.

Table 6: Managed by single predictors' return forecasts

	Return	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}
DP	3.691*** (2.63)	0.549 (0.50)	4.797** (2.35)	0.626 (0.42)	2.637** (2.01)	0.621 (0.55)	1.772 (1.64)	-0.324 (-0.25)	1.685 (1.63)	3.309** (2.23)	1.497 (1.36)	1.223 (1.08)	2.944* (1.92)	1.078 (0.88)	0.211 (0.16)
DY	3.567** (2.44)	0.757 (0.65)	4.461** (2.14)	0.714 (0.46)	2.709** (2.05)	0.898 (0.75)	1.857 (1.62)	-0.309 (-0.24)	1.811* (1.65)	3.577** (2.32)	1.842 (1.62)	1.673 (1.35)	3.265** (2.07)	1.550 (1.18)	0.459 (0.36)
EP	2.377 (1.30)	1.389 (1.12)	2.530 (1.39)	1.184 (0.79)	2.024 (1.26)	1.394 (1.11)	1.630 (1.15)	1.595 (1.06)	1.268 (0.89)	1.331 (0.79)	1.311 (0.97)	0.665 (0.50)	1.421 (0.88)	0.789 (0.62)	1.623 (0.96)
DE	2.375 (0.91)	0.925 (0.56)	3.595 (0.96)	1.794 (0.74)	1.564 (0.79)	0.888 (0.53)	2.073 (1.04)	0.106 (0.06)	1.353 (0.72)	2.991 (1.09)	2.343 (1.20)	2.163 (1.01)	2.505 (0.90)	1.770 (0.77)	0.856 (0.45)
SVAR	2.889 (0.70)	-1.478 (-0.50)	7.178 (0.84)	1.866 (0.28)	-0.280 (-0.07)	-2.510 (-0.83)	1.918 (0.52)	2.652 (0.47)	0.515 (0.19)	-1.108 (-0.32)	-1.624 (-0.42)	-3.077 (-0.97)	-2.430 (-0.78)	-4.175 (-1.28)	-0.726 (-0.13)
BM	4.548*** (3.22)	1.700* (1.67)	5.550*** (2.96)	1.769 (1.45)	3.493*** (2.79)	1.756* (1.69)	2.736** (2.55)	0.907 (0.91)	2.695*** (2.70)	4.138*** (2.87)	2.346** (2.13)	2.242** (2.08)	3.913*** (2.67)	2.212* (1.91)	1.298 (1.23)
NTIS	-0.223 (-0.16)	2.255 (1.18)	0.921 (0.39)	4.566 (1.47)	0.645 (0.37)	2.218 (1.12)	1.364 (0.88)	5.543* (1.80)	0.835 (0.48)	0.114 (0.06)	1.548 (0.83)	1.753 (0.82)	0.060 (0.03)	1.539 (0.73)	5.516 (1.62)
TBL	1.608 (1.39)	2.237** (2.10)	1.965 (1.41)	2.903* (1.75)	1.808 (1.55)	2.193** (2.02)	1.921* (1.83)	3.038* (1.67)	1.419 (1.33)	1.361 (1.06)	2.064* (1.83)	1.800 (1.54)	1.341 (1.04)	1.720 (1.42)	3.336 (1.62)
LTY	1.868 (1.41)	1.066 (0.88)	3.251** (2.08)	2.380 (1.10)	1.511 (1.14)	1.040 (0.84)	1.215 (1.13)	3.258 (1.47)	0.590 (0.51)	0.839 (0.55)	0.819 (0.68)	0.308 (0.21)	0.677 (0.46)	0.188 (0.13)	3.344 (1.38)
LTR	3.007* (1.80)	2.466* (1.66)	3.209** (2.21)	2.494 (1.50)	3.191* (1.70)	2.611 (1.62)	2.674* (1.90)	2.296 (1.17)	3.323* (1.83)	3.189 (1.34)	3.005* (1.65)	2.742 (1.35)	3.069 (1.37)	2.699 (1.37)	2.863* (1.71)
TMS	0.996 (0.70)	2.259* (1.67)	-0.861 (-0.46)	0.567 (0.40)	1.592 (1.13)	2.387* (1.72)	1.745 (1.35)	-0.588 (-0.49)	1.874 (1.38)	1.862 (1.18)	2.251 (1.60)	2.614 (1.64)	2.137 (1.34)	2.786* (1.73)	-0.459 (-0.34)
DFY	1.555 (0.75)	0.331 (0.27)	3.831* (1.88)	2.531 (1.26)	0.638 (0.35)	0.202 (0.16)	1.649 (1.17)	2.505 (0.93)	-0.623 (-0.31)	1.051 (0.45)	1.340 (0.90)	0.418 (0.25)	0.925 (0.40)	0.310 (0.18)	2.568 (1.14)
DFR	-0.564 (-0.32)	2.021 (0.89)	-0.879 (-0.26)	2.657 (0.62)	0.761 (0.34)	2.164 (0.89)	0.826 (0.41)	3.390 (0.82)	-0.510 (-0.27)	-0.103 (-0.04)	1.930 (0.72)	1.444 (0.56)	0.687 (0.29)	2.015 (0.80)	4.325 (0.88)
INFL	1.738 (1.29)	2.033 (1.49)	0.358 (0.24)	0.526 (0.26)	2.245* (1.67)	2.190 (1.59)	1.948 (1.46)	0.654 (0.31)	2.062 (1.37)	1.893 (1.21)	2.175 (1.39)	1.942 (1.29)	1.939 (1.28)	1.975 (1.34)	0.657 (0.34)
IK	5.154*** (3.52)	3.486*** (2.98)	5.889*** (3.97)	3.700*** (2.66)	4.491*** (3.42)	3.533*** (2.97)	4.027*** (3.40)	3.387** (2.23)	3.885*** (3.35)	4.385*** (3.09)	3.590*** (2.92)	3.252*** (2.63)	4.664*** (3.19)	3.620*** (2.68)	3.542** (2.03)

Notes: This table presents the monthly performance of the managed corporate bond market portfolio that uses single predictors' corporate bond market return forecasts as conditioning variables. We calculate the annualized average returns and multifactor alphas of the managed corporate bond market portfolio. The weights in the managed portfolio are proportional to the out-of-sample corporate bond market return forecasts based on single predictors' return forecasts. We conditionally demean the return forecasts and scale the weights in the managed market portfolio to match its conditional standard deviation with that of the corporate bond market portfolio using information available at time t . The alphas are obtained from estimating the regression in Equation (7). Detailed definitions of the factor models are provided in Section 4.2. The Newey & West (1986) adjusted t -statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from December 1991 to December 2022.

Table 7: Transaction costs

Panel A: Turnover and break-even transaction cost										
	Turnover		Break-even TC (bps)							
Managed MKTB	0.347		119							
Panel B: Performance after accounting for proportional transaction costs										
	TC = 0bp		TC = 1bp		TC = 5bps		TC = 10bps		TC = 15bps	
Average return	4.932** (2.48)		4.890** (2.46)		4.724** (2.38)		4.516** (2.28)		4.308** (2.18)	
	α	Utility (%)	α	Utility (%)	α	Utility (%)	α	Utility (%)	α	Utility (%)
CAPMB	2.942** (2.22)	1.915	2.901** (2.19)	1.809	2.740** (2.07)	1.397	2.538* (1.92)	0.909	2.336* (1.77)	0.452
PEADB	6.370*** (2.80)	2.480	6.331*** (2.78)	2.443	6.173*** (2.72)	2.301	5.975*** (2.64)	2.128	5.777** (2.56)	1.963
BOND2	3.858** (2.56)	0.935	3.820** (2.54)	0.907	3.670** (2.44)	0.797	3.483** (2.32)	0.647	3.295** (2.20)	0.501
MKT2	4.180** (2.56)	4.684	4.138** (2.54)	4.549	3.969** (2.44)	4.018	3.759** (2.31)	3.379	3.548** (2.19)	2.767
HKM	2.988** (2.23)	1.998	2.947** (2.20)	1.891	2.783** (2.08)	1.473	2.578* (1.93)	0.979	2.374* (1.77)	0.517
FF2	4.084*** (2.64)	4.840	4.042*** (2.61)	4.710	3.874** (2.51)	4.201	3.664** (2.39)	3.605	3.454** (2.26)	3.033
BOND5	3.294** (2.08)	0.864	3.257** (2.05)	0.841	3.106** (1.96)	0.747	2.918* (1.85)	0.623	2.730* (1.73)	0.504
IPR5	3.005** (2.13)	3.185	2.965** (2.10)	3.073	2.806** (1.99)	2.616	2.606* (1.85)	2.109	2.407* (1.71)	1.570
STOCK5	4.520** (2.37)	5.282	4.476** (2.35)	5.165	4.300** (2.26)	4.695	4.080** (2.15)	4.105	3.860** (2.04)	3.595
FF5	3.980** (2.50)	3.958	3.936** (2.48)	3.889	3.761** (2.38)	3.526	3.543** (2.26)	2.953	3.324** (2.13)	2.392
BS6	3.229** (2.19)	2.125	3.187** (2.16)	2.035	3.016** (2.05)	1.716	2.802* (1.91)	1.358	2.588* (1.77)	0.968
STOCK6	4.314** (2.24)	0.979	4.271** (2.22)	0.929	4.100** (2.13)	0.725	3.885** (2.03)	0.482	3.671* (1.92)	0.284
BS7	3.129** (2.01)	0.664	3.087** (1.99)	0.616	2.920* (1.88)	0.414	2.710* (1.75)	0.161	2.501 (1.62)	-0.064
BS10	3.861** (2.09)	1.016	3.822** (2.07)	0.995	3.667** (1.99)	0.911	3.472* (1.89)	0.808	3.278* (1.80)	0.706

Notes: This table presents the results for the managed corporate bond market portfolio after controlling for the impact of transaction costs. In Panel A, we compute the turnover rate of the timing strategy as the time-series average of all re-balanced trades incurred. We also calculate the break-even proportional transaction cost (in bps) which leads to zero net return. Panel B summarizes statistics of the managed bond market portfolio net of transaction costs. We set proportional transaction costs to 1, 5, 10, and 15 basis points, respectively, and calculate the resulting average returns of the combination forecast-managed bond market portfolio. The alphas are obtained from estimating the regression in Equation (7). Utility is the real-time relative utility gain of the optimal combination strategy relative to strategies without the managed market portfolio for investors. Detailed definitions of the factor models are provided in Section 4.2. The Newey & West (1986) adjusted t -statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from December 1991 to December 2022.

Table 8: Alternative combining method: DMSPE

Panel A: Full-sample forecasting results														
	R^2_{OOS}	p -value	MSPE-adjusted	p -value	Δ CER									
DMSPE	2.043***	<0.00>	3.668***	[0.00]	1.984									
Panel B: Performance of managed portfolio														
	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}
DMSPE	3.566** (2.31)	5.731** (2.55)	4.684*** (2.78)	4.135** (2.36)	3.629** (2.32)	4.175** (2.56)	4.094** (2.41)	3.041** (2.06)	4.526** (2.34)	4.479*** (2.76)	3.983** (2.41)	4.357** (2.20)	3.892** (2.20)	4.818*** (2.62)
Panel C: Performance of enhanced strategies														
	CAPMB	PEADB	BOND2	MKT2	HKM	FF2	BOND5	IPR5	STOCK5	FF5	BS6	STOCK6	BS7	BS10
Panel C.1: Full-sample Sharpe ratio														
SR	0.583	1.060	1.337	0.543	0.652	0.467	1.436	0.681	0.845	0.749	0.951	1.262	1.310	1.631
SR^*	0.747	1.296	1.473	0.761	0.807	0.729	1.542	0.818	1.036	0.963	1.091	1.386	1.409	1.775
ΔSR	0.164	0.236	0.136	0.218	0.155	0.263	0.106	0.137	0.190	0.213	0.140	0.124	0.099	0.144
ω^*	0.432	0.125	0.086	0.696	0.449	0.493	0.067	0.497	0.371	0.463	0.273	0.195	0.165	0.079
Panel C.2: Out-of-sample strategy – Cederburg et al. (2020)’s approach														
SR_{OOS}	0.482	0.953	1.169	0.240	0.524	0.281	0.964	0.312	0.368	0.477	0.461	0.907	0.893	1.023
SR^*_{OOS}	0.665	1.284	1.337	0.530	0.695	0.648	1.114	0.571	0.603	0.761	0.618	1.038	1.004	1.242
ΔSR_{OOS}	0.182**	0.331***	0.167**	0.290***	0.170**	0.366***	0.150***	0.259**	0.234***	0.284***	0.157**	0.132**	0.112**	0.219***
p -value	(0.010)	(0.000)	(0.017)	(0.001)	(0.014)	(0.001)	(0.003)	(0.011)	(0.001)	(0.002)	(0.012)	(0.019)	(0.027)	(0.002)
Utility (%)	3.629	2.205	1.373	4.481	3.766	5.725	1.254	4.076	5.599	6.330	3.317	1.311	1.385	1.526
ω^*_{OOS}	0.270	0.074	0.059	0.654	0.282	0.422	0.042	0.386	0.255	0.341	0.173	0.136	0.108	0.061
Panel C.3: Out-of-sample strategy – Optimal tangency portfolio														
SR_{OOS}	0.562	0.953	1.169	0.245	0.554	-0.023	0.949	0.259	0.410	0.336	0.444	0.926	0.915	0.936
SR^*_{OOS}	0.758	1.284	1.337	0.440	0.759	0.232	1.090	0.597	0.597	0.566	0.601	1.056	1.026	1.165
ΔSR_{OOS}	0.196**	0.331***	0.167**	0.195	0.205**	0.255	0.140***	0.338**	0.187**	0.229***	0.157***	0.131**	0.111**	0.229***
p -value	(0.023)	(0.000)	(0.017)	(0.131)	(0.017)	(0.335)	(0.005)	(0.012)	(0.015)	(0.006)	(0.009)	(0.022)	(0.027)	(0.002)
Utility (%)	0.769	0.435	0.275	2.100	0.811	2.315	0.273	2.012	0.661	1.569	0.592	0.116	0.241	0.452
ω^*_{OOS}	0.270	0.074	0.059	0.654	0.282	0.422	0.042	0.386	0.255	0.341	0.173	0.136	0.108	0.061

Notes: This table presents results for using the discount mean square prediction error (DMSPE) combining method. Panel A shows the results for the time-series evaluation tests, including the out-of-sample R^2 (R^2_{OOS}) of [Campbell & Thompson \(2008\)](#), the MSPE-adjusted statistic of [Clark & West \(2007\)](#) with the standard normal distribution to obtain the one-sided (upper-tail) p -value of the null hypothesis (in square brackets), and annualized certainty equivalent gains (Δ CER). We evaluate the statistical significance of out-of-sample R^2 by using the bootstrap approach of [Welch & Goyal \(2008\)](#) and report the corresponding p -values in angle brackets. Panel B presents the annualized factor alphas of a managed bond market portfolio that uses the DMSPE forecast combining method. The [Newey & West \(1986\)](#) adjusted t -statistics are reported in parentheses. In Panel C, we summarize statistics of enhanced strategies. Panel C.1 reports the full-sample gains in annualized Sharpe ratios in the optimal combination portfolios. SR is the in-sample Sharpe ratio of the optimal combination portfolio implied by a factor model, SR^* is the in-sample Sharpe ratio of the model expanded by the managed bond market portfolio, and ΔSR denotes the difference in Sharpe ratios. ω^* represents the optimal relative weights on the managed bond market portfolio in the optimal combination portfolios. Panels C.2 and C.3 present the results for the out-of-sample combination strategy based on the [Cederburg et al. \(2020\)](#)’s approach and the optimal tangency portfolio, respectively. The optimal investment weights are estimated by using the data available up to time t . We use the subscript OOS to denote the statistics of out-of-sample approaches. To test whether the Sharpe ratio difference is statistically significant, we use the [Jobson & Korkie \(1981\)](#) test with a null hypothesis $H_0 : \Delta SR = 0$ and report the corresponding p -values in parentheses. Utility is the relative utility gain of the optimal combination strategy relative to strategies without the managed market portfolio for investors. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Imposing leverage constraints

	Constraints = [-4, 4]	Constraints = [-3, 3]	Constraints = [-2, 2]	Constraints = [-1, 1]	Constraints = [0, 1]
Returns	4.820** (2.46)	4.508** (2.52)	3.879*** (2.71)	2.719*** (2.78)	3.114*** (3.69)
α_{CAPMB}	2.854** (2.19)	2.646** (2.18)	2.288** (2.19)	1.646** (2.07)	1.250** (2.46)
α_{PEADB}	6.327*** (2.82)	6.100*** (2.91)	5.403*** (3.13)	3.929*** (3.33)	4.253*** (3.87)
α_{BOND2}	3.861*** (2.59)	3.793*** (2.64)	3.460*** (2.68)	2.651*** (2.68)	1.863*** (2.93)
α_{MKT2}	4.034** (2.52)	3.732** (2.56)	3.205*** (2.67)	2.273*** (2.64)	2.412*** (3.45)
α_{HKM}	2.881** (2.18)	2.656** (2.15)	2.279** (2.15)	1.640** (2.02)	1.269** (2.46)
α_{FF2}	3.939*** (2.62)	3.653*** (2.67)	3.130*** (2.78)	2.203*** (2.79)	2.024*** (3.39)
α_{BOND5}	3.292** (2.09)	3.234** (2.14)	3.011** (2.21)	2.303** (2.23)	1.567** (2.42)
α_{IPR5}	2.954** (2.12)	2.721** (2.15)	2.310** (2.18)	1.510** (2.02)	1.765*** (3.32)
α_{STOCK5}	4.342** (2.32)	4.008** (2.32)	3.344** (2.38)	2.346** (2.35)	2.562*** (3.15)
α_{FF5}	3.760** (2.47)	3.424** (2.47)	2.850** (2.51)	2.063*** (2.59)	1.685*** (2.80)
α_{BS6}	3.082** (2.12)	2.829** (2.06)	2.348** (2.01)	1.675* (1.91)	1.334** (2.40)
α_{STOCK6}	4.160** (2.19)	3.864** (2.17)	3.183** (2.20)	2.280** (2.19)	2.442*** (2.99)
α_{BS7}	3.002* (1.95)	2.781* (1.90)	2.268* (1.81)	1.660* (1.74)	1.336** (2.29)
α_{BS10}	3.799** (2.10)	3.695** (2.16)	3.348** (2.26)	2.635** (2.48)	1.790** (2.42)

Notes: This table presents the average returns and annualized factor alphas of the combination forecast-managed market portfolio when imposing leverage constraints. The weights in the managed portfolio are proportional to the out-of-sample corporate bond market return forecasts derived from the mean forecast combination. We conditionally demean the return forecasts and scale the weights in the managed market portfolio to match its conditional standard deviation with that of the corporate bond market portfolio using information available at time t . We restrict the w_t^{COMB} in Equation (6) to the intervals of [-4,4], [-3,3], [-2,2], [-1,1], [0,1]. The last case corresponds to a timing strategy with a short-sale constraint and zero excess leverage. The alphas are obtained from estimating the regression in Equation (7). Detailed definitions of the factor models are provided in Section 4.2. The [Newey & West \(1986\)](#) adjusted t -statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from December 1991 to December 2022.

Table 10: Economic conditions, market states, and the managed portfolio

<i>Panel A: Economic conditions</i>															
	Return	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}
<i>Panel A.1: Industrial production</i>															
Large $ \Delta $	7.161** (2.01)	5.231** (2.06)	8.212** (2.22)	5.897** (2.34)	6.570** (2.06)	5.253** (2.06)	6.204** (2.21)	5.305** (2.18)	4.463* (1.84)	6.553** (2.04)	6.191** (2.21)	5.218** (2.05)	6.307** (1.97)	5.088** (1.99)	5.970** (2.29)
Small $ \Delta $	2.515** (1.97)	0.454 (0.30)	4.278*** (2.70)	1.515 (0.79)	1.554 (1.12)	0.512 (0.33)	1.771 (1.26)	1.051 (0.61)	1.430 (1.12)	2.234 (1.47)	1.550 (1.08)	0.998 (0.64)	2.150 (1.37)	1.003 (0.61)	1.475 (0.74)
<i>Panel A.2: CFNAI</i>															
Large $ \Delta $	5.241** (2.01)	3.633** (2.07)	6.821** (2.29)	4.613** (2.38)	4.655** (2.12)	3.661** (2.06)	4.503** (2.19)	4.620** (2.28)	4.460** (2.37)	4.911* (1.95)	4.347** (2.09)	3.815* (1.91)	4.905* (1.89)	4.113** (1.96)	4.786** (2.12)
Small $ \Delta $	4.634** (2.05)	2.266 (1.16)	5.943** (2.52)	3.132 (1.55)	3.717* (1.81)	2.328 (1.19)	3.676* (1.75)	2.021 (1.10)	1.582 (0.91)	4.137** (1.96)	3.612* (1.70)	2.653 (1.39)	3.763* (1.86)	2.200 (1.16)	2.956 (1.45)
<i>Panel A.3: DP ratio</i>															
Large $ \Delta $	7.684** (2.49)	5.931** (2.53)	9.520*** (2.76)	7.098*** (2.69)	7.051*** (2.63)	5.959** (2.54)	7.110*** (2.62)	6.607** (2.34)	5.524** (2.48)	6.808** (2.49)	6.888** (2.54)	5.762** (2.44)	6.605** (2.46)	5.700** (2.39)	6.772** (2.31)
Small $ \Delta $	2.337 (1.61)	0.099 (0.09)	3.518** (2.21)	0.910 (0.88)	1.450 (1.11)	0.152 (0.13)	1.218 (1.11)	0.303 (0.30)	0.528 (0.42)	2.216 (1.36)	1.171 (1.00)	0.662 (0.53)	2.053 (1.19)	0.573 (0.42)	1.194 (0.89)
<i>Panel A.4: Credit spread</i>															
Large $ \Delta $	6.793* (1.83)	5.227* (1.92)	8.690** (2.17)	6.417** (2.33)	6.294* (1.84)	5.261* (1.92)	5.847** (2.01)	5.950** (2.29)	4.768* (1.80)	6.728* (1.95)	5.892** (2.01)	5.648** (2.03)	6.146* (1.78)	5.158* (1.84)	6.562** (2.37)
Small $ \Delta $	3.120** (2.24)	0.683 (0.44)	4.220*** (2.70)	1.456 (0.83)	2.077 (1.41)	0.735 (0.47)	2.362 (1.61)	0.831 (0.45)	1.293 (0.93)	2.280 (1.56)	2.063 (1.38)	0.760 (0.49)	2.520 (1.63)	1.129 (0.68)	1.310 (0.70)
<i>Panel A.5: Real interest rate</i>															
Large $ \Delta $	5.195*** (2.62)	3.682** (2.21)	6.755*** (2.86)	4.645** (2.31)	4.172** (2.34)	3.788** (2.21)	4.662** (2.52)	4.253** (2.06)	2.523* (1.67)	4.388** (2.25)	4.635** (2.39)	3.860** (2.13)	4.500** (2.26)	4.069** (2.16)	4.853** (2.23)
Small $ \Delta $	4.692* (1.75)	2.255 (1.26)	6.024** (2.15)	3.136* (1.79)	4.187* (1.77)	2.257 (1.26)	3.546* (1.78)	2.415 (1.43)	3.442* (1.75)	4.637* (1.81)	3.386* (1.71)	2.655 (1.43)	4.143 (1.58)	2.245 (1.13)	2.995 (1.46)

(Continued next page.)

Panel B: Market states																
	Return	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}	
<i>Panel B.1: Macroeconomic uncertainty</i>																
Large $ \Delta $	8.990** (2.43)	6.742** (2.53)	10.165*** (2.61)	7.502*** (2.78)	8.145** (2.55)	6.792** (2.53)	8.120*** (2.73)	6.860*** (2.73)	6.258** (2.49)	7.921** (2.33)	8.055*** (2.68)	6.560** (2.39)	7.945** (2.38)	6.652** (2.39)	7.537*** (2.84)	
Small $ \Delta $	0.895 (0.80)	-0.802 (-0.62)	2.490* (1.85)	0.163 (0.10)	0.280 (0.23)	-0.756 (-0.59)	0.072 (0.06)	-0.244 (-0.15)	-0.245 (-0.20)	1.078 (0.83)	-0.051 (-0.04)	-0.133 (-0.10)	0.659 (0.50)	-0.408 (-0.32)	0.213 (0.11)	
<i>Panel B.2: Financial uncertainty</i>																
Large $ \Delta $	7.779** (2.02)	5.835** (2.06)	9.404** (2.32)	6.871** (2.49)	7.353** (2.12)	5.835** (2.05)	6.842** (2.27)	6.408** (2.51)	6.101** (2.25)	7.572** (2.15)	6.776** (2.28)	6.006** (2.13)	7.084** (1.97)	5.615* (1.92)	7.342*** (2.60)	
Small $ \Delta $	2.276 (1.58)	0.238 (0.15)	3.595** (2.18)	1.104 (0.57)	1.146 (0.70)	0.293 (0.18)	1.535 (0.92)	0.540 (0.26)	0.082 (0.06)	1.539 (0.88)	1.337 (0.76)	0.540 (0.33)	1.771 (0.98)	0.862 (0.50)	0.703 (0.35)	
<i>Panel B.3: Real uncertainty</i>																
Large $ \Delta $	8.623** (2.31)	6.282** (2.50)	9.922** (2.53)	7.134*** (2.85)	7.741** (2.43)	6.336** (2.50)	7.364*** (2.62)	7.145*** (2.98)	6.214** (2.55)	7.875** (2.36)	7.237** (2.57)	6.398** (2.50)	7.609** (2.30)	6.188** (2.42)	7.587*** (2.93)	
Small $ \Delta $	1.415 (1.20)	-0.201 (-0.13)	2.937** (2.10)	0.739 (0.41)	0.833 (0.68)	-0.157 (-0.10)	0.969 (0.73)	-0.390 (-0.21)	-0.036 (-0.03)	1.242 (0.89)	0.867 (0.61)	0.152 (0.10)	1.025 (0.69)	0.094 (0.06)	0.268 (0.14)	
<i>Panel B.4: Economic uncertainty</i>																
Large $ \Delta $	7.776** (2.03)	5.104* (1.94)	9.304** (2.28)	6.126** (2.24)	7.164** (2.10)	5.109* (1.93)	6.719** (2.22)	5.463** (2.06)	5.437** (2.07)	7.142** (2.07)	6.771** (2.22)	5.109* (1.93)	6.956** (1.99)	5.029* (1.81)	6.067** (2.11)	
Small $ \Delta $	2.193** (1.97)	0.910 (0.75)	3.571*** (2.80)	1.771 (1.24)	1.272 (1.01)	0.973 (0.79)	1.590 (1.33)	1.312 (0.94)	0.624 (0.52)	1.836 (1.34)	1.294 (1.02)	1.350 (1.06)	1.683 (1.24)	1.274 (1.03)	1.795 (1.13)	
<i>Panel B.5: VIX</i>																
Large $ \Delta $	5.239** (1.99)	4.123** (2.06)	6.767** (2.25)	5.043** (2.32)	4.930** (2.09)	4.128** (2.05)	4.492** (2.08)	4.773** (2.18)	4.337** (2.25)	4.800** (1.98)	4.427** (2.02)	3.985* (1.95)	4.406* (1.75)	3.813* (1.72)	5.222** (2.22)	
Small $ \Delta $	4.622** (2.05)	1.716 (0.99)	5.976*** (2.59)	2.630 (1.50)	3.401* (1.72)	1.791 (1.03)	3.668* (1.90)	1.800 (1.05)	1.591 (0.94)	4.218* (1.95)	3.505* (1.80)	2.402 (1.38)	4.223* (1.95)	2.435 (1.37)	2.434 (1.28)	

Notes: This table presents the average returns and factor alphas of managed bond market portfolios while conditioning on large (above median) versus small (below median) absolute changes ($|\Delta|$) in state variables. To capture changes in economic conditions, we consider five variables, including the industrial production growth, the Chicago Fed National Activity Index (CFNAI), the dividend-to-price ratio, the credit spread (calculated as the yield difference between Moody's seasoned Baa corporate bonds and 10-year constant-maturity Treasury bonds), and the real interest rate (calculated as the difference between the US 3-month T-bill rate and expected inflation that is the 3-month moving average of changes in the US consumer price index), and summarize the results in Panel A. In Panel B, we consider five uncertainty indicators to represent the market states. These variables are the macroeconomic and real uncertainty indexes of [Jurado et al. \(2015\)](#), the financial uncertainty index of [Ludvigson et al. \(2021\)](#), the economic uncertainty index of [Bekaert et al. \(2022\)](#), and the volatility index (VIX). The [Newey & West \(1986\)](#) adjusted t -statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from December 1991 to December 2022.

Table 11: Additional robustness checks

<i>Panel A: Alternative corporate bond market proxies</i>															
	Raw	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}
<i>Panel A.1: The Bloomberg US Corporate Bond Index (sample period: 1986:01 – 2022:12)</i>															
Average Return	4.507*** (2.69)	3.680*** (2.80)	5.963*** (2.73)	4.618*** (3.06)	3.611** (2.55)	3.571*** (2.82)	2.588** (2.08)	3.763** (2.55)	2.696** (2.13)	3.964** (2.48)	2.399* (1.95)	3.893*** (2.88)	3.498** (2.19)	3.757*** (2.73)	4.453*** (2.97)
<i>Panel A.2: The Merrill Lynch Aggregate Bond Market index (sample period: 1986:01 – 2022:12)</i>															
Average Return	3.540** (2.31)	2.101* (1.76)	4.919*** (3.14)	3.273** (2.40)	3.037** (2.22)	2.090* (1.74)	2.606** (2.18)	2.824** (2.02)	2.100* (1.88)	2.997** (2.11)	2.375** (1.97)	2.022* (1.67)	3.358** (2.40)	2.506** (2.02)	3.159** (2.03)
<i>Panel A.3: MKTB constructing with the TRACE-based WRDS data (sample period: 2002:09 – 2022:09)</i>															
Average Return	1.274* (1.90)	1.817*** (2.64)	1.125 (1.61)	2.025** (2.50)	1.777** (2.27)	1.832** (2.57)	1.597** (2.46)	1.372** (2.24)	0.988** (1.99)	1.785** (2.44)	2.073*** (3.07)	1.971*** (2.83)	1.613** (2.26)	1.777*** (2.59)	1.362** (2.20)
<i>Panel B: Excluding specific periods</i>															
	Raw	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}
<i>Panel B.1: Excluding the 2008 global financial crisis</i>															
Crisis period	7.371 (0.46)	6.769 (0.56)	9.511 (0.61)	7.868 (0.72)	9.334 (0.64)	6.088 (0.50)	9.210 (0.63)	12.751 (1.31)	11.871 (1.47)	7.987 (0.65)	9.841 (0.69)	5.524 (0.53)	7.013 (0.53)	6.002 (0.51)	13.642 (1.42)
Non-crisis period	5.327*** (2.90)	3.201** (2.17)	6.801*** (3.18)	4.033** (2.28)	4.556*** (2.85)	3.326** (2.24)	4.211*** (2.65)	3.474** (1.97)	3.013** (2.16)	4.885*** (2.72)	4.112** (2.50)	3.513** (2.23)	4.999*** (2.80)	3.745** (2.30)	3.978** (2.10)
<i>Panel B.2: Excluding the 2008 global financial crisis and the pandemic period</i>															
Crisis period	9.428 (0.70)	8.623 (0.85)	11.786 (0.88)	9.851 (1.06)	11.879 (0.92)	8.007 (0.77)	12.672 (0.98)	14.416 (1.57)	12.375* (1.79)	10.722 (0.95)	13.645 (1.04)	8.129 (0.85)	9.949 (0.83)	8.472 (0.81)	16.593* (1.76)
Non-crisis period	5.151*** (2.83)	3.016** (2.04)	6.614*** (3.17)	3.849** (2.20)	4.284*** (2.70)	3.139** (2.09)	3.895** (2.54)	3.283* (1.91)	2.857** (2.07)	4.584** (2.53)	3.726** (2.31)	3.245** (2.05)	4.720*** (2.60)	3.502** (2.10)	3.645* (1.93)

(Continued next page.)

<i>Panel C: Alternative combination forecasts</i>															
	Raw	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}
<i>Panel C.1: The median combination forecast</i>															
Average Return	3.260** (2.11)	2.263* (1.94)	4.805** (2.52)	3.690** (2.27)	2.704** (2.07)	2.240* (1.87)	2.900** (2.24)	3.341* (1.93)	2.272* (1.75)	3.000* (1.84)	2.767** (2.03)	2.402* (1.71)	2.589 (1.58)	2.047 (1.42)	3.724* (1.78)
<i>Panel C.2: The trimmed-mean combination forecast (top&bottom 1 forecast)</i>															
Average Return	4.584** (2.54)	2.967** (2.38)	5.982*** (2.93)	3.981*** (2.69)	3.940*** (2.61)	3.008** (2.37)	3.940*** (2.77)	3.466** (2.16)	2.876** (2.13)	4.261** (2.39)	3.874*** (2.66)	3.221** (2.27)	4.137** (2.28)	3.171** (2.12)	4.022** (2.19)
<i>Panel C.3: The trimmed-mean combination forecast (top&bottom 2 forecasts)</i>															
Average Return	4.606*** (2.67)	3.187** (2.56)	5.980*** (3.14)	4.250*** (2.86)	4.030*** (2.76)	3.222** (2.54)	4.054*** (2.93)	3.786** (2.32)	3.006** (2.26)	4.213** (2.47)	4.001*** (2.83)	3.302** (2.36)	4.091** (2.38)	3.240** (2.20)	4.325** (2.29)
<i>Panel C.4: The trimmed-mean combination forecast (top&bottom 3 forecasts)</i>															
Average Return	4.657*** (2.79)	3.366*** (2.72)	5.951*** (3.16)	4.386*** (2.94)	4.095*** (2.88)	3.389*** (2.68)	4.162*** (3.04)	3.994** (2.47)	3.149** (2.43)	4.231** (2.52)	4.130*** (2.90)	3.409** (2.43)	4.098** (2.39)	3.330** (2.23)	4.530** (2.37)
<i>Panel C.5: The binary timing strategy with the mean combination forecast</i>															
Average Return	3.658*** (3.72)	1.098* (1.83)	5.137*** (3.97)	1.841** (2.56)	2.768*** (3.14)	1.140* (1.84)	2.084*** (3.16)	1.525** (2.11)	1.714*** (2.90)	2.894*** (2.87)	1.722** (2.53)	1.192* (1.86)	2.861*** (2.78)	1.321* (1.91)	1.961*** (2.58)
<i>Panel D: Alternative estimation scheme</i>															
	Raw	α_{CAPMB}	α_{PEADB}	α_{BOND2}	α_{MKT2}	α_{HKM}	α_{FF2}	α_{BOND5}	α_{IPR5}	α_{STOCK5}	α_{FF5}	α_{BS6}	α_{STOCK6}	α_{BS7}	α_{BS10}
<i>Panel D.1: Initial window length = 120 months</i>															
Average Return	5.438** (2.48)	3.399** (2.26)	6.942*** (2.75)	4.237** (2.45)	4.837** (2.54)	3.485** (2.29)	4.487*** (2.63)	3.947** (2.24)	3.536** (2.35)	5.095** (2.44)	4.454** (2.51)	3.648** (2.24)	5.126** (2.43)	3.888** (2.28)	4.513** (2.24)
<i>Panel D.2: Rolling window estimation</i>															
Average Return	6.223*** (5.41)	5.959*** (4.32)	6.789*** (4.81)	6.504*** (3.59)	6.318*** (5.13)	6.076*** (4.37)	5.924*** (4.75)	6.104*** (3.04)	6.282*** (4.59)	6.908*** (5.22)	6.181*** (4.74)	6.662*** (4.48)	6.937*** (5.08)	6.724*** (4.35)	6.698*** (3.34)

Notes: This table summarizes results from a battery of additional robustness tests. We calculate the annualized average returns and multifactor alphas of the managed corporate bond market portfolio. The weights in the managed portfolio are proportional to the out-of-sample corporate bond market return forecasts derived from the mean forecast combination. We conditionally demean the return forecasts and scale the weights in the managed market portfolio to match its conditional standard deviation with that of the corporate bond market portfolio using information available at time t . The alphas are obtained from estimating the regression in Equation (7). Detailed definitions of the factor models are provided in Section 4.2. In Panel A, we consider three alternative proxies for the corporate bond market portfolio, including the Bloomberg US Corporate Bond Index (sample period: January 1986 to December 2022), the Merrill Lynch Aggregate Bond Market index (sample period: January 1986 to December 2022), and the corporate bond market factor constructed by using the TRACE database from the Wharton Research Data Services (WRDS) bond database (sample period: September 2002 to September 2022). In Panel B, we exclude specific crisis periods during which the managed corporate bond market portfolio performs noticeably well. We first exclude January 2008 to June 2009, a period corresponding to the 2008 global financial crisis. Next, we further exclude the COVID-19 pandemic period from January 2020 to April 2020. Panel C presents statistics for the managed bond market portfolio when using alternative simple averaging schemes, including the median and trimmed-mean combination, to obtain the return forecasts (Panels C.1 to C.4). In Panel C.5, we consider a binary timing strategy, which invests either 100% in the bond market portfolio when the conditioning variable exceeds its conditional mean or 0% in all other periods. In Panel D, we consider alternative estimation schemes to produce market return forecasts instead of using a 5-year recursive estimation approach. To do so, we use a relatively longer recursive estimation window of 120 months (Panel D.1) and a rolling window estimation scheme of a fixed length of 5 years (Panel D.2). The Newey & West (1986) adjusted t -statistics are reported in parentheses and *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A Definitions of predictors

1. Dividend-price ratio (log), DP: the difference between the logarithm of a 12-month moving average sum of dividends paid by the S&P 500 firms and the logarithm of stock price level (S&P 500 index).
2. Dividend yield (log), DY: the difference between the logarithm of the 12-month moving average sum of dividends and the logarithm of lagged stock price level (S&P 500 index).
3. Earnings-price ratio (log), EP: the logarithm of the ratio of the 12-month moving average sum of earnings on the S&P 500 index divided by the stock prices (S&P 500 index).
4. Dividend-payout ratio (log), DE: the difference between the logarithm of dividends and the logarithm of earnings.
5. Stock return variance, SVAR: the sum of squared daily excess returns on the S&P 500 index during the past month.
6. Book-to-market ratio, BM: the ratio of book value to market value for the Dow Jones Industrial Average index (DJIA).
7. Net equity expansion, NTIS: the ratio of the 12-month moving sum of net issues by New York Stock Exchange (NYSE)-listed firms divided by the total end-of-year market capitalization of NYSE stocks.
8. Treasury bill rate, TBL: the interest rate on the three-month Treasury bill of the secondary market.
9. Long-term yield, LTY: the yield on the long-term government bond.
10. Long-term return, LTR: the long-term rate of government bond returns.
11. Term spread, TMS: the difference between the yield on long-term government bond and the Treasury bill rate.
12. Default yield spread, DFY: the difference between the BAA- and AAA-rated corporate bond yields.
13. Default return spread, DFR: the difference between the long-term corporate bond returns and the long-term government bond returns.
14. Inflation, INFL: the growth rate in the Consumer Price Index from the Bureau of Labor Statistics. At each point in time, we calculate the most recent growth rate by using data observable in real time. This vintage data is collected from the ALFRED database.
15. Investment-to-capital ratio, IK: the investment-to-capital ratio of aggregate (private non-residential fixed) investment to aggregate capital for the entire economy. At each point in

time, we calculate the most recent estimate of the ratio by using data observable in real time. This vintage data is collected from the ALFRED database.

Appendix B Definitions of bond and equity factors

Appendix B.1 Corporate bond factors

1. Corporate bond market factor, MKTB ([Dickerson, Mueller, & Robotti, 2023](#)): average return of all corporate bond in excess of the one-month risk-free rate of return.
2. Bond carry factor, CRY ([Israella et al., 2018](#); [Kelly et al., 2023](#)): independently sort bonds into 5×5 portfolios according to their ratings and bond credit spreads. CRY is the average return difference between the the high-carry portfolios and the low-carry portfolios across all rating quintile portfolios.
3. Bond default risk factor, DEF ([Fama & French, 1993](#)): the return difference between the market portfolio of long-term corporate bond returns (the composite portfolio on the corporate bond module of Ibbotson Associates) and the long-term government bond.
4. Bond duration factor, DUR ([Israella et al., 2018](#); [Kelly et al., 2023](#)): independently sort bonds into 5×5 portfolios according to their ratings and bond duration. DUR is the average return difference between the the high-duration portfolios and the low-duration portfolios across all rating quintile portfolios.
5. Bond long-term reversal factor, LTR ([Bali et al., 2021](#)): dependently sort sorts bond into $3 \times 3 \times 3$ portfolios according to their ratings, maturity and the cumulative returns in the previous 48 to 13 months. LTR is the average return difference between the low-long-term-reversal portfolios and the high-long-term-reversal portfolios across 9 rating-maturity terciles.
6. Bond momentum factor, MOMB ([Jostova et al., 2013](#)): independently sort bonds into 5×5 portfolios according to their ratings and the cumulative returns in the previous 12 to 2 months. MOMB is the average return difference between the the high-bond-momentum portfolios and the low-bond-momentum portfolios across all rating quintile portfolios.
7. Bond earnings announcement drift factor, PEADB ([Nozawa et al., 2024](#)):
8. Bond short-term reversal factor, STR ([Bali et al., 2021](#)): independently sort bonds into 5×5 portfolios according to their ratings and returns in prior month. STR is the average return difference between the the short-term-loser portfolios and the short-term-winner portfolios across all rating quintile portfolios.

9. Bond term structure risk factor, TERM (Fama & French, 1993): the difference between the monthly long-term government bond return (from Ibbotson Associates) and the one-month Treasury-Bill rate of return.
10. Bond value factor, VAL (Israella et al., 2018; Houweling & Van Zundert, 2017): independently sort bonds into 2×3 portfolios according to their size and value. By using the cross-sectional regression of bond credit spreads on their ratings, maturity and the three-month change in credit spread, the value characteristic is computed as the percentage difference between the actual and fitted credit spread. VAL is the average return difference between the the high-value portfolios and the low-value portfolios across two size portfolios.

Appendix B.2 Equity factors

1. Equity market factor, MKTS (Fama & French, 1992, 2015): the value-weighted returns of all firms listed on the NYSE, AMEX, or NASDAQ in excess of the one-month risk-free rate of return.
2. Size factor, SMB (Fama & French, 1992, 2015): the difference in returns between small and large capitalization stocks.
3. Equity value factor, HML (Fama & French, 1992, 2015): the difference in returns between high and low book-to-market stocks.
4. Equity momentum factor, MOMS (Carhart, 1997): the difference in returns between winner and loser stocks.
5. Intermediary capital risk factor, HKM (He et al., 2017): the value-weighted investment returns for a portfolio of the New York Fed primary dealers' publicly-traded holding companies.
6. Liquidity factor, LIQ (Pástor & Stambaugh, 2003): the value-weighted returns for the long-short portfolio from sorting on historical liquidity betas.
7. Profitability factor, RMW (Fama & French, 2015): the difference in returns between high and low profitability (measured by the ratio of adjusted revenue to the book equity) stocks.
8. Investment factor, CMA (Fama & French, 2015): the difference in returns between stocks with low change in total assets and stocks with high change in total assets.