Aggregate Default Risk and Corporate Bond Returns*

Linjia Song and Ruijing Yang†

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ABSTRACT

We construct a default risk index using Partial Least Squares (PLS) to aggregate 23 default risk proxies and find that it significantly predicts returns of corporate bond portfolios, both in-sample and out-of-sample. The PLS default risk index outperforms individual proxies and generates substantial economic gains for mean-variance investors. Additionally, we document that PLS is superior to other methods such as Principal Component Analysis (PCA) and Forecast Combination (FC). The predictive power of the PLS default risk index primarily stems from firms with lower credit ratings. Moreover, aggregating individual default risk proxies using PLS can also predict macroeconomic indicators.

Keywords: time-series prediction, corporate bond returns, aggregate default risk, Partial Least Squares, financial ratios

JEL classification: G11, G12, G13, G14, G17

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†Linjia Song is at Xiamen University, songlinjia@xmu.edu.cn. Ruijing Yang is at The Chinese University of Hong Kong, emails: RuijingYang@link.cuhk.edu.hk.

1 Introduction

Default risk, representing the likelihood and severity of losses from issuer default, is crucial in determining bond prices and returns, . However, accurately measuring default risk is challenging. Previous studies have used different proxies for default risk, such as financial ratios, expected default loss, equity volatility, credit ratings, etc. (see, for example, Altman (1968), Ohlson (1980), Elton, Gruber, Agrawal, and Mann (2001), Campbell and Taksler (2003), Avramov, Chordia, Jostova, and Philipov (2009)). Although default risk measures have been used to explain the cross section of corporate bond returns, less attention has been paid to the time-series return predictability of corporate bond portfolios. Extending the literature on predicting corporate bond returns is important as the corporate bond market has become increasingly large and significant, with more than \$10.3 trillion outstanding in the United States as of 2022, accounting for 22.3% of the total bond market.[1] Understanding the dynamics of corporate bond returns can have implications for asset allocation, risk management, and macroeconomic policy. Our paper provides new and robust findings that aggregating individual default risk measures can predict returns of corporate bond portfolios.

In this paper, we calculate 23 default risk measures at the firm level, aggregate them to the market level, and use Partial Least Squares (PLS) to form a single default risk index (PLS default risk index). We find that this PLS default risk index can predict future returns of corporate bond portfolios, both in-sample and out-of-sample. Specifically, the 23 individual default risk measures include: working capital to assets ratio (WCAPAT), retained earnings to assets ratio (REAT), earnings before interest and tax to assets ratio (EBITAT), market value of equity to liabilities ratio (MELT), sales to assets ratio (SALEAT), adjusted firm size as defined in Ohlson (1980) (SIZE), liabilities to assets ratio (LTAT), current liabilities to current assets ratio (LCTACT), indicator of whether liabilities exceed assets as defined in Ohlson (1980) (OENEG), net income to assets ratio (NIAT), cash flow from operations to liabilities ratio (FUTL), indicator of whether the net income has been negative for the past two consecutive years as in Ohlson (1980) (INTWO), change of net income as measured in Ohlson (1980) (CHIN), market-to-book ratio (MB), cash to assets ratio (CASHAT), relative firm size (RSIZE), excess stock return relative to S&P500 index (EXRET), standard deviation of the daily stock return for the past 3 months (SIGMA), natural logarithm of stock prices truncated above at \$15 (PRICE), default probability as defined Hannan and Hanweck (1988) (HHDP), distance to default as calculated in Bharath and Shumway (2008) (DD), number ratings as in Avramov et al. (2009) (RATING), risk-neutral default probability as in Carr and Wu (2011) (CWDP). We choose these measures based on seminal papers in the

[1] According to SIFMA, https://www.sifma.org.

field of default risk, and all these measures can be calculated using publicly available data.

We first examine the in-sample predictive power of the PLS default risk index for returns of corporate bond portfolios across different credit ratings and maturities. Specifically, we classify corporate bonds into four categories by their credit ratings and three categories by their maturities. Our findings indicate that the PLS default risk index can positively predict returns for all corporate bond portfolios, aligning with the risk-return channel, which suggests that higher default risk corresponds to higher future corporate bond returns. Specifically, for the return of the corporate bond portfolio including all filtered bonds, the in-sample estimated coefficient is 0.62 with a t-statistic of 3.88 when the forecasting horizon is one month. A one-standard-deviation increase in the PLS default risk index is associated with a 0.62% increase in corporate bond returns. This increase is 124% of the average monthly return of this portfolio, which is 0.50%, indicating that the predictability is economically significant. When the forecasting horizon extends to three months, the predictive power of the PLS default risk index remains robust, with an estimated coefficient of 0.56 and a t-statistic of 5.83. Compared to individual default risk proxies, the PLS default risk index substantially outperforms each one of them. For the portfolio that includes all filtered bonds, the highest adjusted R^2 achieved by an individual default risk proxy is 9.25% for a one-month forecasting horizon and 17.22% for a three-month horizon. In contrast, the adjusted R^2 of the PLS default risk index is 11.31% for the one-month horizon and 23.74% for the three-month horizon.

Interestingly, we find that the predictive power of the PLS default risk index varies across different corporate bond portfolios. Specifically, the predictive power is stronger for returns of corporate bond portfolios with lower credit ratings and shorter maturities. For example, when the forecasting horizon is one month, the adjusted R^2 for the corporate bond portfolio with a rating higher than AA and a maturity longer than 10 years is 5.30%, whereas for the portfolio with a rating lower than BBB and a maturity of less than 3 years, it is as high as 14.84%. When the forecasting horizon extends to three months, the difference becomes even more pronounced, with the adjusted R^2 for the former portfolio at 9.88% and for the latter at 36.86%.

Previous studies, such as Lin, Wu, and Zhou (2018), have investigated the role of macroeconomic variables in corporate bond return predictability. To demonstrate that the PLS default risk index provides independent information beyond these macroeconomic variables, we control for the macroeconomic variables from Goyal and Welch (2008) and past stock market returns in a multivariate regression. Following Chen, Tang, Yao, and Zhou (2021), we include 8 out of the 14 macroeconomic variables from Goyal and Welch (2008) to avoid multicollinearity. Our findings indicate that the predictability of the PLS default risk index is not subsumed by these variables, and its coefficients remain sizable. In untabulated tables, we confirm that the predictive power remains significant both statistically and economically when we control for the previously mentioned variables individually.

The in-sample predictability derived from the full sample data may suffer from potential look-ahead bias. To provide a more accurate evaluation of the predictability of aggregate default risk measures, we conduct out-of-sample forecast analyses for the 15 aggregate default risk measures. The out-of-sample tests use only information available at time t to obtain return forecasts for time $t+1$, reflecting the situations faced by real-world investors. We compare the predicted values based on the aggregate default risk measures with those based on the prevailing mean and calculate the out-of-sample R^2 following Campbell and Thompson (2008). Specifically, we evaluate the out-of-sample return predictability for the return of each corporate bond portfolio. When the forecasting horizon is one month, we find that the PLS default risk index has positive out-of-sample R^2s for all portfolios, all of which are statistically significant at the 5% level or better. Furthermore, the PLS default risk index significantly outperforms individual default risk proxies in most cases. For the portfolio including all corporate bonds, the highest out-of-sample R^2 achieved by an individual default risk proxy is 4.78% for a one-month forecasting horizon and 9.86% for a three-month horizon. In contrast, the PLS default risk index achieves an out-of-sample R^2 of 7.28% for the one-month horizon and 14.67% for the three-month horizon.

Consistent with our in-sample findings, we document that out-of-sample predictability is stronger for corporate bond portfolios with lower credit ratings and shorter maturities on average. Additionally, the improvement provided by the PLS default risk index is more pronounced in these portfolios. For instance, in the portfolio with a rating higher than AA and a maturity longer than 10 years, the out-of-sample R^2 of the PLS default risk index is only 1.27% when the forecasting horizon is one month. In this case, the highest out-of-sample R^2 achieved by an individual default risk proxy is 3.26%, which is higher than that of the PLS default risk index. In contrast, for the portfolio with a rating lower than BBB and a maturity of less than 3 years, the out-of-sample R^2 of the PLS default risk index is 9.96% when the forecasting horizon is one month, whereas the highest out-of-sample R^2 achieved by an individual default risk proxy is only 4.55%. Although the PLS default risk index may underperform individual default risk proxies in certain cases, it generally outperforms them on average. This conclusion is supported by its significant outperformance in the portfolio that includes all corporate bonds and the substantial improvements observed in many instances.

Besides PLS, other widely used dimension reduction methods such as Principal Component Analysis (PCA) and Forecast Combination (FC) have also been shown to be efficient in return prediction. We compare PLS with these two methods and find that PLS, at least in our setting, is superior to PCA and FC, although these two methods can also generate positive out-of-sample R^2s. For example, for returns of the portfolio including all filtered corporate bonds, the out-of-sample R^2 for PLS is 7.28% when the forecasting horizon is one month and 14.67% when the forecasting horizon is three months. In contrast, the out-of-sample R^2 is 1.70% (2.46%) for PCA (FC) when the forecasting horizon is one month and 3.46% (5.32%) when the forecasting horizon is three months. Furthermore, when the forecasting horizon is one month, PLS outperforms PCA and FC in every corporate bond portfolio we considered. When the forecasting horizon is three months, PLS outperforms PCA and FC in 19 out of 20 corporate bond portfolios, with the only exception being the portfolio with a rating higher than AA and a maturity longer than 10 years.

In addition to the in-sample and out-of-sample predictability tests, we also evaluate the economic value of the PLS default risk index following Campbell and Thompson (2008) and Rapach, Ringgenberg, and Zhou (2016). Assuming a mean-variance investor who allocates wealth between a corporate bond portfolio and risk-free bills, we calculate optimal portfolio weights based on return forecasts derived from the PLS default risk index. Subsequently, we compute the certainty equivalent return (CER) gains and the Sharpe ratio of the portfolio. Our findings indicate that employing the PLS default risk measure results in significantly positive utility gains and improved risk-adjusted returns compared to strategies using the prevailing means to forecast returns.

Furthermore, we extend our analysis by constructing two PLS default risk indexes using firms with different credit ratings. We classify firms into investment-grade and high-yield categories based on whether their S&P rating is at least BBB. Subsequently, we construct two PLS default risk indexes: $\mathrm{D}^{\mathrm{PLS}}_{\mathrm{IG}}$ and $\mathrm{D}^{\mathrm{PLS}}_{\mathrm{HY}}$. Our findings reveal that the PLS default risk index obtained from firms with lower credit ratings exhibits significantly stronger predictive power not only for returns of corporate bond portfolios with lower credit ratings but also for those with higher credit ratings. Finally, we provide evidence that aggregating individual default risk proxies can also predict macroeconomic conditions, such as the industrial production index (IPI), unemployment rate (UR), and the CBOE volatility index (VIX). This finding reaffirms that aggregating individual default risk proxies captures the aggregate default risk of the entire market. This partially explains the economic channel underlying return predictability.

Our paper contributes to three strands of literature. First, our paper contributes to the literature about the time-series prediction of the corporate bond returns. Although studies about the prediction of corporate bond market returns can be traced back to Keim and Stambaugh (1986), Fama and French (1989), and Chang and Huang (1990). This literature still receives much less attention than those about the prediction of the equity premium motivated by the seminal work of Goyal and Welch (2008). In recent studies, Hong, Lin, and Wu (2012) document that the past stock market return can predict future corporate bond returns both in-sample and out-of-sample. Greenwood and Hanson (2013) argue that issuer quality is a negative signal for future corporate bond returns. Huang, Rossi, and Wang (2015b) document a negative relation between the stock sentiment index of Baker and Wurgler (2006) and future corporate bond returns. Lin et al. (2018) use the iterated weighted-average model to combine 27 variables and show that this combined measure has good predictive power for corporate bond returns. Our paper extends this literature by aggregating 23 individual default risk proxies to form a single default risk index and utilizes this index to predict future corporate bond returns. We find that this default risk index is a robust predictor for future corporate bond returns, exhibiting strong predictability both in-sample and out-of-sample.

Second, our paper contributes to the literature about the relation between default risk and the corporate bond returns. As a key determinant of corporate bond returns, default risk proxies show significant cross-sectional predictability for corporate bond returns. One of the famous two-factor model in Fama and French (1993), DEF, is a default risk factor. Gebhardt, Hvidkjaer, and Swaminathan (2005) further document that the default beta is important in explaining the individual bond returns. Campbell and Taksler (2003) use the market-based distance-to-default to explain the cross section of corporate bond returns. They find that the distance-to-default has more explanatory power than credit ratings and that it captures both systematic and idiosyncratic components of default risk. A recent study by Bao, Hou, and Zhang (2023) study this relationship from the time-series perspective. They find that their systematic default risk measure can significantly predict future corporate bond index returns both in-sample and out-of-sample. Our paper contributes to this literature by aggregating existing cross-sectional default risk proxies to the market level and testing their in-sample and out-of-sample predictabilities. We find that while some of these proxies exhibit significant predictability with correct signs in-sample, few of them demonstrate robustness in out-of-sample tests. Furthermore, aggregating these individual default risk proxies allows for the formation of a robust default risk index that positively predicts future corporate bond returns.

Finally, our paper also builds upon the literature about how to measure default risks. Early studies like Altman (1968) and Ohlson (1980) use accounting-based measures to construct default risk scores, which are widely accepted. Later studies use other data to provide incremental information and implement alternative models to increase the accuracy of the estimation of the default risk. For example, Shumway (2001) use the hazard model and market-based data to forecast bankruptcy. Chava and Jarrow (2004) find that is is important to include industry effects when predicting defaults. Campbell, Hilscher, and Szilagyi (2008) input accounting and market variables into a dynamic logit model to estimate firms' failure probability. Our paper demonstrates that, rather than relying on a single measure, aggregating individual default risk measures to extract their common component as an index can significantly enhance predictive performance.

The rest of our paper is organized as follows. Section 2 describes the data and variables. Section 3 presents empirical findings, including in-sample and out-of-sample predictability of aggregate default risk measures, comparison with macroeconomic variables, and implications for asset allocation. Section 4 performs robustness tests and further discusses our results. Section 5 concludes the paper.

2 Data and Variables

2.1 Corporate Bond Returns

We obtain corporate bond returns from WRDS, which are calculated using TRACE Standard and TRACE Enhanced datasets. Our target variable, RET_EOM, provides larger sample coverage. To ensure consistency with existing literature, we apply standard filters to our sample. First, we only retain corporate bonds with maturities between 2 and 30 years. Second, we exclude convertible bonds. Third, we limit our sample to corporate bonds with prices between 50 and 150. Fourth, we require the time gap between the current record and the previous record to be less than 6 months. Finally, we retain corporate bonds with an outstanding amount of at least 250 million. We construct corporate bond portfolios based on credit ratings and maturities. Specifically, we classify corporate bonds into four rating groups: higher than AA (>= AA), A, BBB, and lower than BBB (<BBB). Additionally, we categorize corporate bonds into three maturity groups: Short, Medium, and Long, comprising corporate bonds maturing in less than 3 years, 4-10 years, and longer than 10 years, respectively. This process results in 20 portfolios, in which tests will be conducted separately. In each corporate bond portfolio, the portfolio return is calculated as the weighted average of individual corporate bond returns, with the weighting scheme based on the dollar amount outstanding, determined by the product of the bond's price and the amount outstanding.

Table A1 presents the summary statistics of returns for different corporate bond portfolios. The monthly average return of the portfolio including all filtered corporate bonds is

0.50%. Mean returns and volatilities of corporate bond portfolios tend to be higher when the portfolio has lower credit ratings and longer maturities. For instance, the portfolio with a rating higher than AA and a maturity of less than 3 years exhibits an average return of 0.26% and a standard deviation of 0.88%. In contrast, the portfolio with a rating lower than BBB and a maturity longer than 10 years demonstrates an average return of 1% and a standard deviation of 3.64%.

2.2 Default Risk Proxies

We obtain 23 measures for the default risk from the existing literature, including working capital to assets ratio (WCAPAT), retained earnings to assets ratio (REAT), earnings before interest and tax to assets ratio (EBITAT), market value of equity to liabilities ratio (MELT), sales to assets ratio (SALEAT), adjusted firm size as defined in Ohlson (1980) (SIZE), liabilities to assets ratio (LTAT), current liabilities to current assets ratio (LCTACT), indicator of whether liabilities exceed assets as defined in Ohlson (1980) (OENEG), net income to assets ratio (NIAT), cash flow from operations to liabilities ratio (FUTL), indicator of whether the net income has been negative for the past two consecutive years as in Ohlson (1980) (INTWO), change of net income as measured in Ohlson (1980) (CHIN), market-to-book ratio (MB), cash to assets ratio (CASHAT), relative firm size (RSIZE), excess stock return relative to S&P500 index (EXRET), standard deviation of the daily stock return for the past 3 months (SIGMA), natural logarithm of stock prices truncated above at $15 (PRICE), default probability as defined Hannan and Hanweck (1988) (HHDP), distance to default as calculated in Bharath and Shumway (2008) (DD), number ratings as in Avramov et al. (2009) (RATING), risk-neutral default probability as in Carr and Wu (2011) (CWDP). All default risk measures are computed using public-available data. The detailed definition and constructions of the default risk measures can be found in the Variable Definition.

The construction of predictors involves five steps: First, we calculate the 23 default risk measures mentioned above at the firm level. Second, we winsorize the firm-level measures at the 0.1% level for each month to remove outliers. Third, we aggregate these measures at the market level by taking the equal-weighted average across firms for each month.[2] Fourth, we run the following regression and take the residuals to detrend these measures:

$$D_{i,t} = \alpha_i + \beta\, t + u_{i,t} \quad \text{for} \quad t = 0, ..., T \tag{1}$$

[2]Using equal-weighting to aggregate measures at the firm level to the market level is a common practice in the time-series prediction literature, see also Rapach et al. (2016), Jondeau, Zhang, and Zhu (2019), and Cao, Li, Zhan, and Zhou (2022).

where $D_{i,t}$ is the i^{th} aggregate default risk measure, t represents a month indicator, which starts at 0 at the beginning of the sample period, and $\hat{u}_{i,t}$ is the detrended value of the i^th aggregate default risk measure. As shown in Table A3, many aggregate default risk measures exhibit significant time trends, emphasizing the necessity of the detrend process. Finally, we standardize these measures to have zero mean and unit variance.

Table 1 presents the summary statistics for the 23 aggregate default risk measures. All measures have been detrended and standardized to have zero mean and unit variance. This table indicates that aggregate default risk measures are very persistent. With the exception of the past excess stock return (EXRET), which has a first-order autocorrelation coefficient of only 0.2, the minimum first-order autocorrelation coefficient among the remaining measures is 0.66. The correlation matrix for these measures can be found in Table A2.

[Insert Table 1]

2.3 PLS Default Risk Index

We aggregate the individual default risk proxies using the Partial Least Squares (PLS) method, which was introduced by Herman (1966) and applied to the finance domain by Kelly and Pruitt (2013) and Kelly and Pruitt (2015). Since then, this method has been utilized from various perspectives to aggregate individual measures into a single measure to predict future stock market returns. For example, Huang, Jiang, Tu, and Zhou (2015a) aggregate sentiment index components from Baker and Wurgler (2006) to form a target-relevant sentiment index, documenting that this index can significantly predict stock returns. Similarly, Huang, Li, and Wang (2021) and Chen et al. (2021) predicte aggregate stock market returns by aggregating individual measures for disagreement and investor attention, respectively.

Specifically, we implement the PLS method through the following two steps: First, We run a time-series regression of each individual default risk proxy on the realized corporate bond returns as the following:

$$D_{i,t} = \pi_0 + \pi_i R_{t+1} + u_{i,t} \tag{2}$$

where $D_{i,t}$ is i^{th} individual default risk proxy at time t, R_{t+1} is the realized corporate bond return at time $t+1$. The coefficient π_i captures the sensitivity of the proxy $D_{i,t}$ to the future corporate bond return. Second, we run a cross-sectional regression of $D_{i,t}$ on π_i for each month:

$$D_{i,t} = \alpha_t + D_t \pi_i + v_{i,t} \tag{3}$$

where the regression slope D_t represents the PLS default risk index in month t. In Figure 1, we plot the PLS default risk index obtained from the full sample. Intuitively, we observe that the PLS default risk index peaked during the 2008 financial crisis and the 2020 COVID-19 pandemic, periods when firms were extremely vulnerable to default risk.

[**Insert Figure 1**]

3 Empirical Results

3.1 In-Sample Prediction

In this section, we test the predictive power of the PLS aggregate default measure on the excess returns of corporate bond index in the US market, which is calculated as the logarithm excess return of the corporate bond index to T-bill return. We run the following predictive regression:

$$r_{t+h} = \alpha + \beta \times D_{i,t} + \epsilon_{t+h} \tag{4}$$

where r_{t+h} is the average excess return of the corporate bond index over the forecasting horizon h. In our paper, $h = 1$, 3, and 6 months. $D_{i,t}$ is the PLS aggregate default risk index at month t. All aggregate default risk measures are first detrended and then standardized to have 0 mean and unit variance. We compute the t-statistics using the Newey and West (1987) correction with h lags. The hypothesis testing is $H_0 : \beta = 0, H_1 : \beta \neq 0$. Rejecting the null hypothesis $\beta = 0$ indicates that this measure has significant predictive power for future corporate bond index returns in-sample. Considering the potential differences in the nature of corporate bonds with different credit rating and maturity, we analyze the returns of each portfolio and present the results separately.

Panel A of Table 2 demonstrates the in-sample predictability of the PLS aggregate default risk measure for the returns of various corporate bond groups over the next month. For the bond market index, the coefficient on the default risk index is 0.62, with a t-statistic of 3.88.

In addition to the bond market index, we also construct bond indexes based on bonds with different credit ratings. Specifically, we group the corporate bonds into four categories: higher than AA, A, BB, and lower than BB. The coefficients of the bond indexes on the

PLS aggregate default risk measure are 0.44, 0.57, 0.66, and 0.94, respectively. These results suggest that the predictive power of the aggregate default risk measure is stronger for firms with lower credit ratings. Corporate bonds issued by firms with lower credit ratings are more likely to be affected by default risk. We further classify the corporate bonds into different groups based on their maturity: short, medium, and long. Using the average return for these different groups as the dependent variable, the coefficients are 0.43 for short-term bonds, 0.64 for medium-term bonds, and 0.84 for long-term bonds. The return predictive power is stronger for corporate bonds with longer maturities, which are associated with higher default risk.

In Panel B of Table 2, we extend the forecast horizon to 3 months. The return predictability of the PLS default risk measure persists across different bond portfolios. The coefficient of the bond market index on the PLS default risk measure is 0.56, with a t-statistic of 5.83. These results indicate that the predictive power of the PLS default risk measure persists for at least 3 months.

[**Insert Table 2**]

3.2 Out-of-Sample Prediction

Although our previous tests demonstrate the predictability of the PLS aggregate default risk measure on corporate bond index returns through the in-sample predictive regression, these results may be misleading due to the presence of "look-ahead" bias in the in-sample predictive regressions. In the previous regressions, we use all available data to estimate the coefficients β, which can lead to an overestimation of the predictive power. However, real-world investors can only use data available up to the point of making predictions. To address this issue and assess the out-of-sample predictability of the PLS aggregate default risk measure, we conduct the out-of-sample tests in this section.

In the out-of-sample tests, we obtain the predicted value of r_{t+1} based only on information available at time t, using the following equation:

$$\hat{r}_{t+1|t} = \hat{\alpha}_t + \hat{\beta}_t D_t \tag{5}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are estimated from the in-sample predictive regression of Equation (1) using data available through time t. D_t is the PLS aggregate default risk measure at time t. We estimate $\hat{\alpha}_t$ and $\hat{\beta}_t$ based on an expanding estimation window, i.e., we obtain the fitted value using all data available up to time t.[3]

We then compare the model-based predicted value with a benchmark, which assumes that the return is not predictable. The predicted value of the benchmark is set to be the prevailing mean of the return based on information through time t:

$$\bar{r}_{t+1|t} = \frac{1}{t}\sum_{k=1}^{t} r_k \tag{6}$$

We compare the mean squared forecast error (MSFE) of the model-based predicted value with the benchmark using the out-of-sample R^2 statistics proposed by Campbell and Thompson (2008):

$$R^2_{\mathrm{OS}} = 1 - \frac{\sum_{t=T_0}^{T}(r_t - \hat{r}_{t+1|t})}{\sum_{t=T_0}^{T}(r_t - \bar{r}_{t+1|t})} \tag{7}$$

where T_0 is the starting time of the out-of-sample forecast period. We divided our entire sample into two equal parts and start our out-of-sample tests from January 2010. The R^2_{OS} measures the proportional reduction in the mean squared forecast error (MSFE) for the prediction that uses the model-based predicted return compared to the benchmark forecast using the prevailing mean, which assumes that returns are not predictable. A higher R^2_{OS} indicates that the model-based predictions are closer to the actual values on average, indicating better forecast performance. To evaluate whether the model-based predictions yield statistically significant improvements in the mean squared forecast error (MSFE), we propose the following hypothesis test:$H_0 : R^2_{\mathrm{OS}} \leq 0$, $H_1 : R^2_{\mathrm{OS}} > 0$. We conduct this hypothesis test using the Clark and West (2007) test and calculate the corresponding t-statistics. It is important to note that the Clark and West (2007) test is one-tailed, so the t-statistics are 1.282, 1.645, and 2.326 for significance levels of 10%, 5%, and 1%, respectively.

[Insert Table 3]

Panel A of Table 3 presents the out-of-sample predictability of the PLS aggregate default risk measures for corporate bond index returns. When the forecasting period is one month, the R^2_{OS} is 7.28% for aggregate market index and the t-statistic is 2,61, which is significant at 1% level. The out-of-sample performance is different for corporate bonds with different ratings. The R^2_{OS} is 3.44% for bonds with rating higher than AA, 5.81% for bonds rated A,

[3]To avoid the look-ahead bias, we ensure that the detrending, standardization, and estimation processes are all conducted only on the training data. When making predictions at time t, we make sure that no information beyond t is leaked into the forecasting process.

6.56% for bonds rated BBB, and 8.33% for bonds rated lower than BBB. The R^2_{OS} is positive and statistically significant for all maturity-rating groups.

If we examine the return predictive power for bond return over a longer horizon, the results are even stronger, The R^2_{OS} for aggregate bond return over the future tree months is 14.67% and statistically significant. Therefore, the return predictive power of aggregate default risk measure persists over longer horizon.

3.3 In Comparison with Economic Variables

In previous analyses, we have shown that the aggregate measure from individual firm default risk measures is a robust and persistent predictor of corporate bond index returns. Lin et al. (2018) employs the iterated combination model to combine variables to predict corporate bond market returns, including several macroeconomic variables documented in Goyal and Welch (2008). In this section, we aim to control for several economic variables documented in Goyal and Welch (2008) to assess whether the predictability of the PLS default risk measure remains after controlling for these factors. Specifically, we run the following predictive regression:

$$r_{t,t+h} = \alpha + \beta \times D_t + \phi X_t + \epsilon_{t,t+h} \tag{8}$$

where r_{t+h} is the average excess return of the corporate bond portfolio over the forecasting horizon h, where $h = 1$, 3, and 6 months. D_t is the PLS default risk measure at month t. X_t represents the vector of selected economic variables from Goyal and Welch (2008).

We obtain macroeconomic data from Amit Goyal's website [4] and calculate the 14 variables. We find that the two pairs of variables have extremely high correlation coefficients (over 0.9), which are TMS and TBL, and DP and DY in our sample periods. To avoid multicollinearity, we only keep one of them in each pair. In the end, we keep 12 variables, and they are: book-to-market ratio (BM), long-term yield (LTY), net equity expansion (NTIS), inflation (INFL), long-term return (LTR), stock return volatility (SVAR), log dividend yield (DY), log earnings-price ratio (EP), log dividend-payout ratio (DE), term spread (TMS), default return spread (DFY), and default yield spread (DFR). Since Hong et al. (2012) find that the past stock market return is also a predictor of corporate bond returns, we also include the stock market excess return (MKTRF) as an additional control.

Table 4 shows that while the magnitude of coefficients decreases to some extent, the in-

[4] https://docs.google.com/spreadsheets/d/1bM7vCWd3WOt95Sf9qjLPZjoiafgF_8EG/edit#gid=407859737

sample predictability of the PLS index remains significant even when controlling for macroeconomic variables from Goyal and Welch (2008), as well as the excess stock market return. In contrast to stock market returns, where predictors usually have small adjusted R^2, corporate bond index returns are highly predictable, especially in longer forecasting horizons. For example, as shown in column 3 (6) of Table 4, on the semi-annual horizon, the adjusted R^2 can reach as high as 42.29 for corporate bond market index.

[Insert Table 4]

3.4 Model Comparison

Besides PLS, there are other dimension reduction methods applied in the finance domain. For example, Ludvigson and Ng (2007) and Ludvigson and Ng (2009) apply the principal component analysis (PCA) to aggregate macroeconomic variables to forecast stock and bond returns, respectively. Neely, Rapach, Tu, and Zhou (2014) combine 14 macroeconomic variables from Goyal and Welch (2008) and 14 technical indicators using PCA to predict market excess returns. In addition to PCA, the forecast combination (FC) is also widely used to aggregate information from individual measures and reduce forecast volatility. Rapach, Strauss, and Zhou (2010) demonstrate that combining the forecasts of macroeconomic variables documented in Goyal and Welch (2008) can lead to significant out-of-sample gains.

In this section, we compare the out-of-sample predictability of PLS to PCA and FC. Specifically, for each corporate bond portfolio, we use these three methods to combine the 23 individual default risk proxies and compare their out-of-sample predictability by examining their out-of-sample R-squares. By construction, PCA constructs the composite variable to explain the maximum variability in individual default risk proxies by giving different proxies different weights based on their variances, but it does not incorporate information relevant to the target. In contrast, although FC utilizes the information of the target, it treats all individual default risk proxies equally. PLS, in comparison, not only incorporates information from the target but also gives more weight to proxies that are more sensitive to the target. Therefore, PLS should perform superior to the aforementioned two methods.

Table 5 presents the comparison results. Although PCA and FC can generate positive out-of-sample R^2s, indicating that their predictions are better than the prevailing mean, PLS performs significantly better than them in almost all corporate bond portfolios.[5] For

[5] The exception is the portfolio including corporate bonds with ratings higher than AA and maturities longer than 10 years

example, for the portfolio including all filtered corporate bonds, PCA and FC achieve out-of-sample R^2s of 1.70% (3.46%) and 2.46% (5.32%) when the forecasting horizon is one month (three months), respectively. In comparison, PLS achieves out-of-sample R^2s of 7.28% (14.67%) for the same horizon. Comparing their out-of-sample predictability across each corporate bond portfolio, we find that the average out-of-sample R^2s generated by PLS is 3.15 times that by PCA and 1.72 times that by FC, indicating a significant improvement in the forecasting performance.

[Insert Table 5]

3.5 Asset Allocation Implications

We have presented considerable evidence indicating that the PLS aggregate default risk measure exhibits robust predictive power for corporate bond index returns both in-sample and out-of-sample. It is important to assess whether this predictive ability can have promising implications for the asset allocation process. In this subsection, we explore whether the use of information from the aggregate PLS measure can deliver substantial economic value to mean-variance investors.

Following Campbell and Thompson (2008) and Rapach et al. (2016), we consider a mean-variance investor who allocates her wealth between the corporate bond index and the risk-free bills. With a forecast horizon of h, the optimal weight for her to invest in the corporate bond index is given by:

$$w_t = \frac{1}{\gamma}\frac{\hat{r}_{t,t+h}}{\hat{\sigma}^2_{t,t+h}} \tag{9}$$

where γ is the relative risk aversion coefficient of the investor, $\hat{r}_{t,t+h}$ is the excess return prediction of the corporate bond index over the forecast horizon,[6] and $\hat{\sigma}^2_{t,t+h}$ is the forecast of the variance of the corporate bond index excess return. Following Campbell and Thompson (2008), we use the sample variance of a 10-year moving window to obtain the variance forecast. We assume that the portfolio rebalancing frequency aligns with the forecast horizon h. For example, if the forecast horizon is 3 months, the investor will use the PLS default risk measure to forecast the cumulative returns of the corporate bond index for the subsequent 3 months and allocate her assets based on the prediction. At the end of each quarter, the investor will update her predictions and rebalance her portfolio accordingly.

[6]It is worth noting that in the in-sample and out-of-sample prediction in Section 3.1 and 3.2, our targets are average returns over the forecasting periods. In this section, our targets are cumulative returns over the forecasting periods.

We consider two different scenarios, each designed for different types of investors. In the first scenario, we consider a relatively typical investor with a relative risk aversion coefficient γ of 3, who has the flexibility to use leverage up to 4 times and is subject to short-sale constraints. Therefore, the optimal weight for her to invest in risky assets will be limited to a range between 0 and 4. In the second scenario, we examine a more risk-averse investor with a relative risk aversion coefficient of 5, who can employ leverage up to 2 times and is also constrained by short-sale restrictions.

For the metrics to assess portfolio performance, we use the certainty equivalent return gain (CER gain) and the Sharpe ratio (S_a). The certainty equivalent return is defined as:

$$\mathrm{CER} = \bar{r}_p - 0.5\gamma\sigma_p^2 \tag{10}$$

where $\bar{r}_p$ and σ_p^2 are the mean and variance of the portfolio return over the forecast horizon, respectively. The CER is the risk-free rate that an investor is willing to accept to hold the risky portfolio.

The utility gain from using the aggregate PLS default risk measure to forecast future excess returns of the corporate bond index is defined as the CER gain:

$$\mathrm{CER\,gain} = \mathrm{CER}_m - \mathrm{CER}_0 \tag{11}$$

where CER_m is the CER if the investor uses the PLS default risk measure to make predictions and form the portfolio. CER_0 is calculated assuming that the investor uses the prevailing mean to forecast future excess returns of the corporate bond index and form the portfolio. The CER gain represents the utility gain when an investor assumes that returns are predictable compared to assuming that they are not. We annualize the CER gain for different forecast horizons, so that it can be interpreted as the management fee an investor is willing to pay for access to the information of the PLS default risk measure to forecast future returns of the corporate bond index.

In addition to the CER gain, we also use the commonly used performance metric, the Sharpe ratio, to assess the utility gain of investors. The Sharpe ratio is defined as:

$$S_a = \frac{\bar{r}_p - r_f}{\sigma_p} \tag{12}$$

where $\bar{r}_p$ and σ_p are the mean and standard deviation of the portfolio return, and r_f is the risk-free return.

[Insert Table 6]

Table 6 demonstrates the asset allocation implications of using the PLS default risk measure. In Panel A, for an investor with a relative risk aversion coefficient of 3 who can employ up to 4 times leverage, using the PLS default risk measure to time the corporate bond market leads to considerable annualized CER gains across different forecasting horizons. Specifically, when predicting the return of the corporate bond market index at the monthly frequency, the annualized CER gain is 7.43. Similar positive utility gains are observed when forecasting the corporate bond return with different rating and maturity. Except for short-term bonds with rating lower than BBB, the CER gain is positive for all groups.

Furthermore, comparing the Sharpe ratios between the benchmark and the PLS index strategy reveals significant increases. For example, for the market bond index, using the PLS measure achieves a Sharpe ratio of 0.59, whereas the prevailing mean strategy only yields a Sharpe ratio of 0.30. This gap in Sharpe ratio is persistent across different bond groups.

Panel B of Table 6 shows the utility gain for a more conservative investor with a relative risk aversion coefficient of 5 and a maximum leverage of 2 times. Although the CER gains decrease in absolute terms, it is 3.28% annually for aggregate bond market return, which is considered significant according to Lin et al. (2018). Together with the reduction in absolute utility gain, the potential risk of the PLS default risk strategy also diminishes, as evidenced by similar magnitudes of the Sharpe ratio between Panel A and Panel B.

4 Robustness and Discussions

4.1 Aggregate Default Risk across Firms with Different Credit Ratings

In our baseline analysis, we aggregate default risk measures across the entire market by taking the equal-weighted average of measures at the firm level. However, considering the availability of credit rating data, particularly for the US market, we explore whether aggregating default risk measures across firms with different credit ratings yields different predictability for corporate bond index returns.

We obtain credit ratings of US firms from the Compustat database (S&P Credit Ratings database for data after 2017) and merge them with our original database. Firms with credit ratings not lower than BBB are considered investment-grade (IG), while those lower than BBB are categorized as high-yield (HY). We then construct two aggregate PLS default risk rmeasures for firms with different credit ratings: PLS_{IG} for investment-grade firms and PLS_{HY} for high-yield firms. Subsequently, we test their out-of-sample predictability for returns of investment-grade and high-yield corporate bond indices separately.

Table 7 shows that although PLS_{IG} maintains some out-of-sample predictability for IG corporate bond index returns, it loses predictive power for HY corporate bond index returns over longer forecasting horizons. For example, R^2_{OS} of PLS_{IG} becomes negative when the forecasting horizon is 3 or 6 months. In contrast, PLS_{HY} exhibits significantly stronger out-of-sample predictability than PLS_{IG}, not only for HY corporate bond index returns but also for IG corporate bond index returns. Its predictive power even exceeds that of the aggregate default risk measure in our baseline results.

The results in Table 7 suggest that the predictive power of the aggregate PLS default risk measure primarily stems from firms with low credit ratings. However, since not all firms are rated by rating agencies, aggregating default risk measures for firms with different credit ratings may result in information loss. Hence, we do not further aggregate default risk measures by specific rating groups, as the firm coverage within each group may be insufficient for enough representativeness. Given that aggregating default risk measures of firms with lower credit ratings can provide stronger out-of-sample predictive power, the whole-market aggregate default risk remains a strong and robust predictor for US corporate bond index returns.

[Insert Table 7]

4.2 Predictability for Macroeconomic Indicators

Although the individual default risk measures included in our analysis are widely accepted as proxies for the default risk, we have not yet provided direct evidence whether the PLS default risk index measure the market level default risk. To address this concern, in this subsection, we investigate whether the PLS default risk index can also predict macroeconomic indicators.

Specifically, we consider six macroeconomic indicators that are closely related to default risk: the Chicago Fed National Activity Index (CFNAI), the Smooth Recession Probability (SRP), Aruoba, Diebold, and Scotti (2009) Business Conditions Index (ADSI), unemployment rate (UR), the CBOE Volatility Index (VIX), and the Industrial Production Index (IPI). The CFNAI is a monthly economic indicator designed to gauge overall economic activity in the United States. A higher CFNAI suggests that the economy is expanding at a faster pace than its long-term average. The SRP is designed to assess the likelihood of a recession in the United States. A higher SRP indicates an increased probability of the economy entering a recession. The ADSI is a real-time, high-frequency economic indicator designed to track business conditions in the United States. A higher ADS Index signifies stronger economic conditions. The IPI offers a real-time assessment of the US economy by aggregating various indicators. When the IPI is higher, it suggests increased industrial output, which often correlates with higher demand, improved business confidence, and overall economic expansion. The UR is a monthly indicator designed to evaluate the percentage of the labor force that is unemployed and actively seeking employment. If market-level default risk is higher, and some firms do default in the future, this would result in job losses, causing the unemployment rate to increase. The VIX estimates the expected volatility of the stock market over the next month, based on S&P 500 index options. Higher values of the CBOE VIX indicate increased market volatility and uncertainty, which are typically associated with higher market-level default risk. Thus, if the market-level default risk is elevated, the CBOE VIX should also be higher, reflecting increased volatility and uncertainty in the market.

If the PLS default risk index actually measures the market-level default risk, we should expect that the PLS default risk index should positively forecast SRP, UR, and VIX, and negatively forecast CFNAI, ADSI, and IPI, since the default risk generally associates with weaker economic performance and financial instability. Table 8 presents the in-sample predictability of the PLS default risk index for predicting the above mentioned macroeconomic indicators. PLS default risk index demonstrates strong in-sample predictability, with coefficients consistent with our hypothesis and statistically significant. For example, a one standard deviation increase in the PLS default risk index is associated with a 0.43 standard deviation increase of the SRP and 0.49 standard deviation increase of the VIX.

[**Insert Table 8**]

5 Conclusion

In this paper, we aggregate 23 individual default risk proxies to the market level using the partial least squares (PLS) method to form a single PLS default risk index. We document that this PLS default risk index can significantly predict corporate bond returns, both in-sample and out-of-sample. The predictability of the PLS default risk index remains robust after controlling for macroeconomic variables and past stock returns and is significantly stronger than other dimension reduction methods such as principal component analysis (PCA) and forecast combination (FC). Furthermore, it has significant implications for asset allocation, providing mean-variance investors with considerable utility gains and improved Sharpe ratios. When decomposing by firms' credit ratings, we find that the predictability of the PLS default risk index primarily stems from the information of firms with lower credit ratings. Finally, we provide evidence that aggregating individual default risk proxies can also forecast macroeconomic indicators.

Future research could explore the predictability of default risk measures for corporate bond returns across different market segments, such as ESG corporate bond indices. Additionally, investigating the relationship between aggregate default risk measures and macroeconomic indicators could provide further insights into the broader economic implications of corporate bond market dynamics. Moreover, examining the robustness of these findings across international markets would be valuable in validating the global applicability of the aggregate default risk measures.

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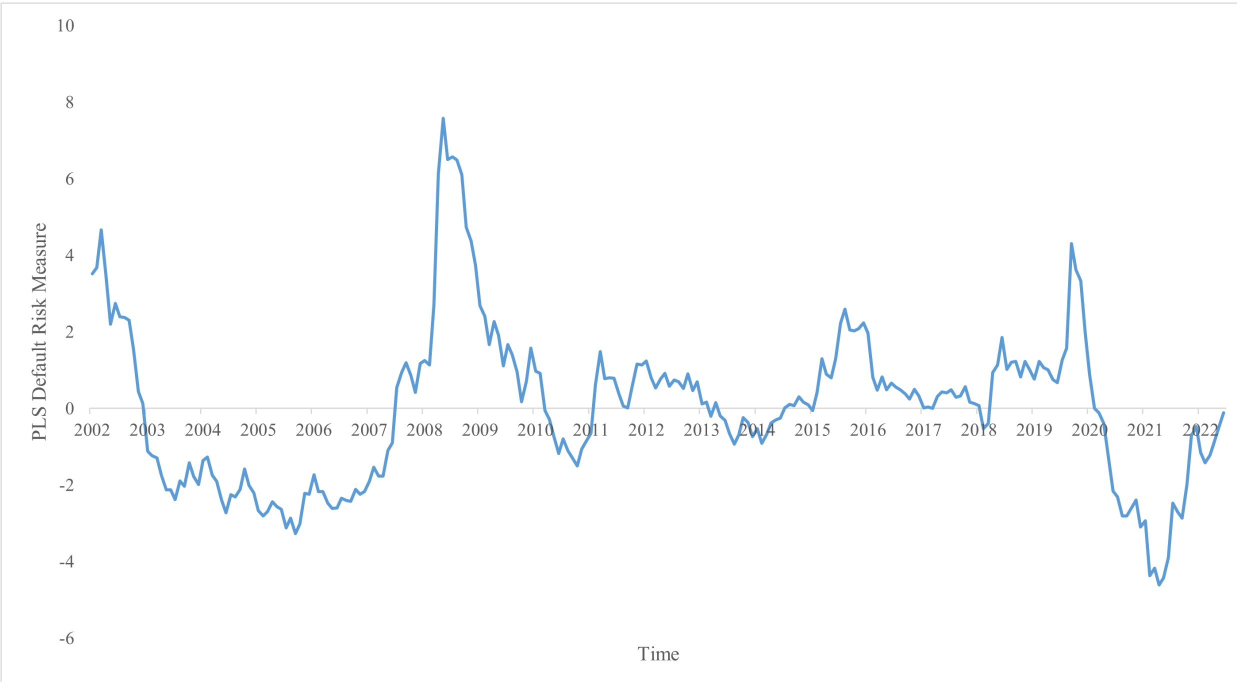
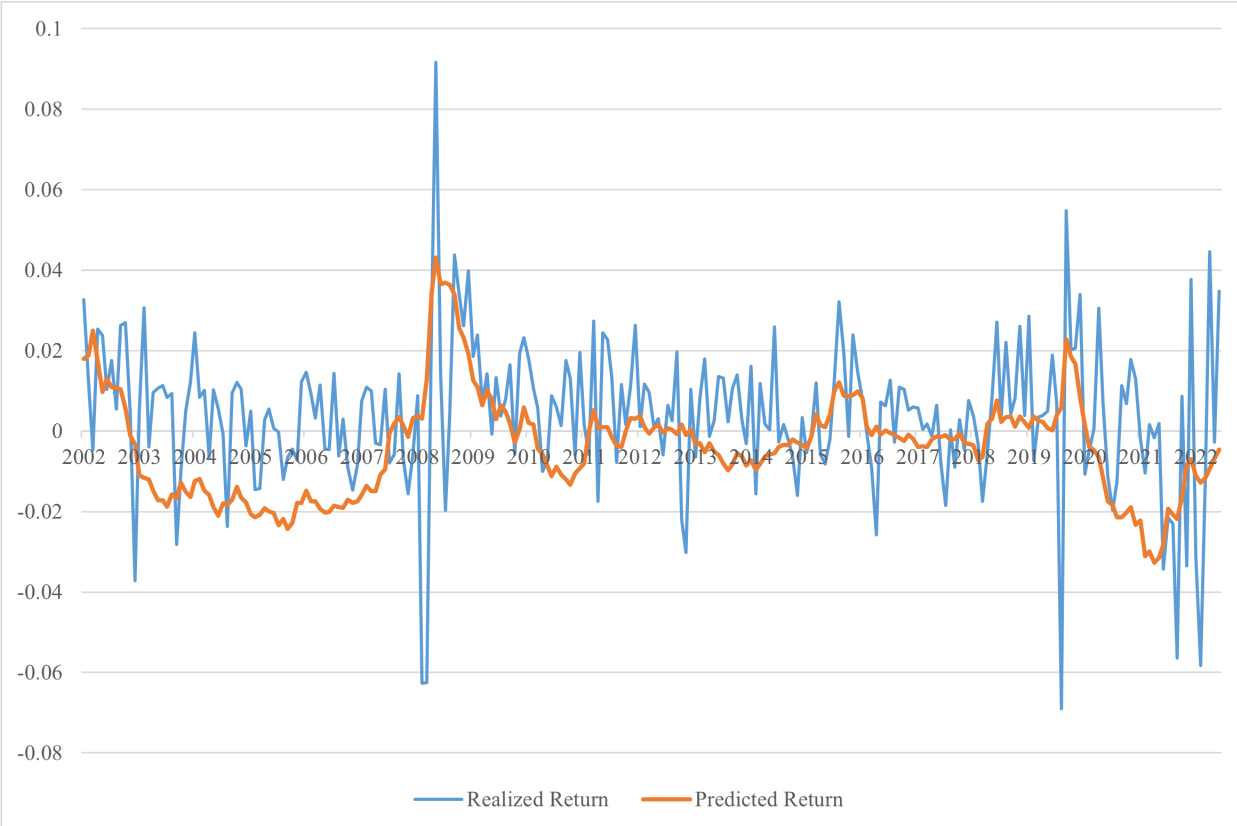
Figure 1. Time-Series of the PLS Default Risk Measure



(a) Prices

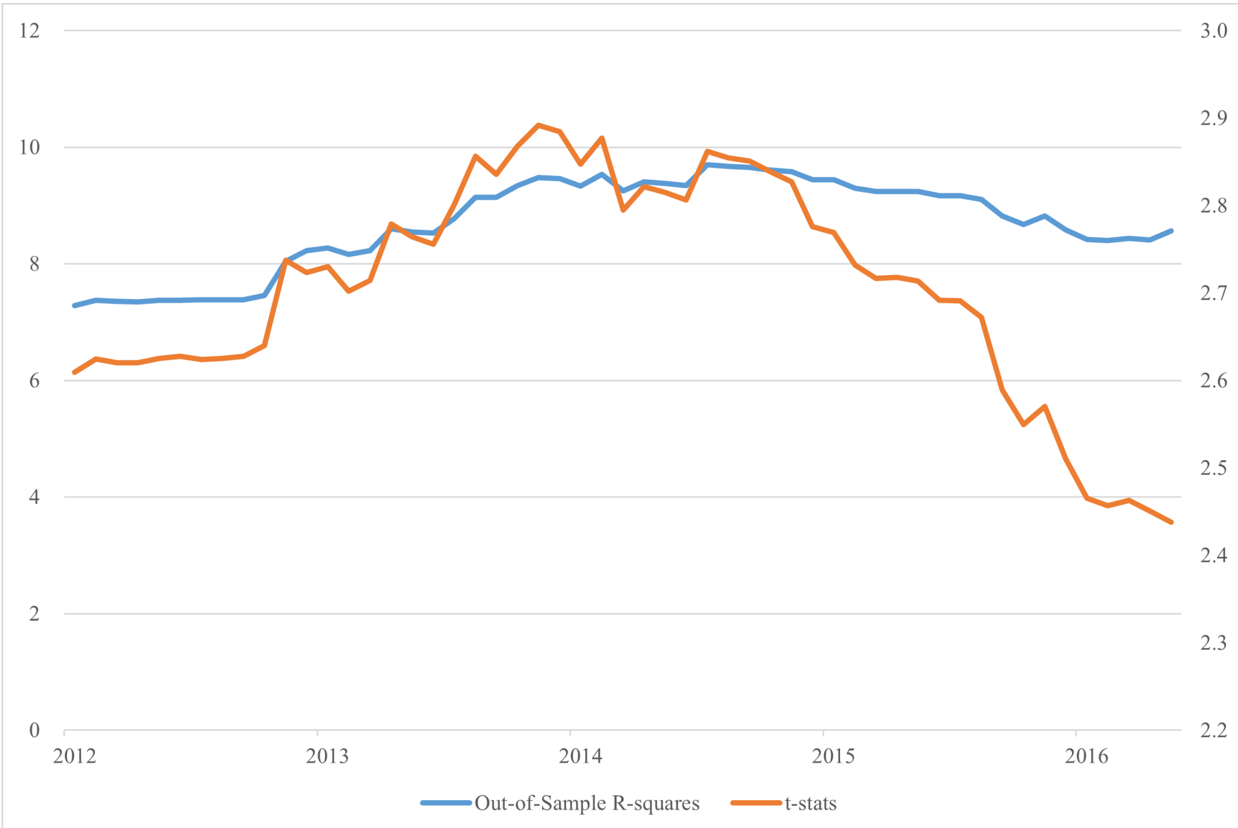
Figure 1: This figure presents the time series of the PLS default risk measure. The PLS default risk measure is calculated by aggregating 23 individual default risk measures, disciplined by the returns of the corporate bond portfolio, which includes all corporate bonds in our sample for the next month. The sample period extends from July 2002 to December 2022.

Figure 2. Comparison of Realized Return and Predicted Return



This figure illustrates the time series of the realized returns of the corporate bond portfolio, which includes all corporate bonds in our sample, alongside the predicted returns using the PLS default risk measure. The parameters used to calculate the predicted returns are derived from the entire sample. The blue line represents the realized returns, while the orange line represents the predicted returns. The sample period spans from July 2002 to December 2022. The forecasting horizon is 1 month.

Figure 3. $R^2_{\mathbf{OS}}$ for Different Starting Periods of the Out-of-Sample Tests



This figure displays the time series of $R^2_{\rm OS}$ of the PLS default risk index when starting the out-of-sample tests from July 2012 to January 2013. The forecasting horizon is one month.

Table 1
Summary Statistics

This table reports the minimum, lower quartile, median, upper quartile, maximum, skewness, and the first-order autocorrelation coefficient of 23 aggregate default risk measures. The definitions of these measures can be found in the Variable Definition. All variables are detrended and standardized to have zero mean and unit variance. The sample period is from July 2022 to December 2022.

	Min	Lower Quartile	Median	Upper Quartile	Max	Skewness	$\rho(1)$
WCAPAT	-2.40	-0.69	-0.17	0.65	3.12	0.57	0.96
REAT	-2.07	-0.66	-0.15	0.77	2.71	0.28	0.98
EBITAT	-2.61	-0.65	0.00	0.76	2.32	-0.17	0.92
MELT	-3.84	-0.50	0.21	0.75	1.49	-1.18	0.96
SALEAT	-2.08	-0.69	0.03	0.57	3.32	0.37	0.90
SIZE	-2.50	-0.63	-0.05	0.68	2.26	-0.01	0.93
LTAT	-2.10	-0.93	0.11	0.82	2.05	-0.18	0.98
LCTACT	-1.86	-0.86	-0.11	0.65	2.57	0.49	0.97
OENEG	-1.71	-0.84	-0.18	0.58	3.02	0.69	0.93
NIAT	-1.88	-0.87	-0.03	0.93	2.02	0.06	0.97
FUTL	-2.25	-0.64	0.00	0.65	2.42	0.05	0.66
INTWO	-1.91	-0.61	-0.09	0.40	3.34	0.79	0.94
CHIN	-2.27	-0.59	-0.09	0.66	2.73	0.37	0.96
MB	-1.25	-0.88	-0.14	0.66	2.81	0.85	0.98
CASHAT	-3.28	-0.50	0.15	0.57	3.09	-0.63	0.97
RSIZE	-2.91	-0.52	0.01	0.46	2.75	-0.12	0.93
EXRET	-3.58	-0.60	0.03	0.68	2.62	-0.29	0.20
SIGMA	-1.00	-0.59	-0.39	0.31	4.90	2.48	0.91
PRICE	-5.47	-0.40	0.22	0.58	1.44	-1.84	0.95
HHDP	-2.01	-0.73	0.01	0.66	3.29	0.16	0.95
DD	-1.80	-0.98	-0.05	0.86	2.19	0.16	0.95
RATING	-3.60	-0.70	0.21	0.71	1.65	-1.15	0.97
CWDP	-1.38	-0.65	-0.24	0.29	5.92	2.39	0.86

Table 2
In-Sample Predictability

This table reports the results of the following predictive regression:

$$r_{t,t+h} = \alpha + \beta \times D_t + \epsilon_{t,t+h}$$

where r_{t+h} is the average excess returns of corporate bond portfolios over the forecasting horizon h, where $h = 1$ and 3 months. D_t is the PLS default risk measure at month t. We classify corporate bonds into four groups by their ratings: higher than AA (>=AA), A, BBB, and lower than BBB (<BBB). We classify corporate bonds into three groups by their maturity: Short, Medium, and Long includes corporate bonds mature less than 3 years, 4-10 years, and longer than 10 years, respectively. Panel A (B) shows the results for the in-sample predictability when $h = 1$ ($h = 3$). The sample period is from July 2002 to December 2022. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: In-Sample Predictability for $h = 1$						
		All	>=AA	A	BBB	<BBB
All	$\hat{\beta}$	0.62***	0.44***	0.57***	0.66***	0.94***
	t-stats	3.88	2.95	3.16	4.07	4.15
	Adj.R^2	11.31	7.01	9.52	10.92	12.35
Short	$\hat{\beta}$	0.43***	0.27***	0.37***	0.44***	0.86***
	t-stats	4.32	3.24	3.67	4.33	4.05
	Adj.R^2	15.83	9.42	13.79	15.46	14.84
Medium	$\hat{\beta}$	0.64***	0.45***	0.56***	0.66***	0.93***
	t-stats	4.05	2.69	3.09	4.19	3.95
	Adj.R^2	12.20	6.83	9.87	11.39	10.89
Long	$\hat{\beta}$	0.84***	0.70**	0.80***	0.90***	1.24***
	t-stats	3.18	2.37	2.69	3.63	4.83
	Adj.R^2	8.10	5.30	7.05	8.51	11.11
Panel B: In-Sample Predictability for $h = 3$						
		All	>=AA	A	BBB	<BBB
All	$\hat{\beta}$	0.56***	0.36***	0.48***	0.61***	0.93***
	t-stats	5.83	3.81	4.75	5.97	7.15
	Adj.R^2	23.74	13.08	18.65	24.35	31.70
Short	$\hat{\beta}$	0.40***	0.22***	0.32***	0.43***	0.86***
	t-stats	7.33	5.11	6.00	7.19	7.12
	Adj.R^2	34.23	17.98	27.94	36.13	36.86
Medium	$\hat{\beta}$	0.58***	0.35***	0.47***	0.61***	0.93***
	t-stats	6.32	3.93	4.94	6.34	6.73
	Adj.R^2	25.79	11.88	18.94	25.69	29.20
Long	$\hat{\beta}$	0.72***	0.55***	0.66***	0.80***	1.19***
	t-stats	4.63	3.28	4.09	4.99	7.77
	Adj.R^2	16.45	9.88	13.85	18.34	27.16

Table 3
Out-of-Sample Predictability

This table reports the out-of-sample predictability of each aggregate default risk measure. We report the out-of-sample R^2 (R^2_{OS}) and the t-statistics based on the Clark and West (2007) test. The whole sample period is from July 2022 to December 2022. We start our out-of-sample test from July 2012. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Out of Sample Predictability for $h = 1$						
		All	>=AA	A	BBB	<BBB
All	R^2_{OS}	7.28***	3.44**	5.81**	6.56***	8.33***
	t-stats	2.61	1.74	2.32	2.48	3.32
Short	R^2_{OS}	13.14***	9.19***	13.30***	11.84***	9.96***
	t-stats	3.78	3.15	3.77	3.62	3.83
Medium	R^2_{OS}	9.07***	5.00**	7.51***	7.72***	7.08***
	t-stats	3.06	2.16	2.75	2.80	3.21
Long	R^2_{OS}	3.71**	1.27**	2.94**	3.83**	6.29**
	t-stats	1.84	1.33	1.74	1.82	2.32
Panel B: Out of Sample Predictability for $h = 3$						
		All	>=AA	A	BBB	<BBB
All	R^2_{OS}	14.67***	3.34*	9.02**	13.77***	26.02***
	t-stats	2.65	1.57	2.25	2.52	3.44
Short	R^2_{OS}	29.76***	13.92***	22.99***	28.71***	28.90***
	t-stats	3.58	2.67	3.34	3.46	4.01
Medium	R^2_{OS}	19.36***	3.36**	11.42***	16.63***	24.35***
	t-stats	3.05	1.70	2.55	2.81	3.49
Long	R^2_{OS}	6.38**	-2.25	3.64**	7.43**	18.99***
	t-stats	1.87	1.02	1.67	1.86	2.46

Table 4
Comparison with Macro Variables

This table reports the results of the following predictive regression:

$$r_{t,t+h} = \alpha + \beta D_t + \phi X_t + \epsilon_{t,t+h}$$

where r_{t+h} is the average excess returns of the corporate bond portfolio including all corporate bonds in our sample over the forecasting horizon h, where $h = 1$, 3, and 6. D_t is the PLS aggregate default measure at month t. X_t represents the vector of selected economic variables from Goyal and Welch (2008) and the excess stock market return. The selected macroeconomic variables are: book-to-market ratio (BM), long-term return (LTR), stock return volatility (SVAR), log dividend price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), term spread (TMS), default return spread (DFY). We also control the stock market excess return (MKTRF). We follow Chen et al. (2021) to select variables in order to avoid the multicollinearity. All measures are standardized to have zero mean and unit variance. The sample period is from December 1996 to December 2022. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$h = 1$	$h = 3$	$h = 6$
D^{PLS}	0.53**	0.50***	0.47***
	(2.15)	(2.96)	(2.79)
BM	0.44	0.41**	0.24
	(1.57)	(1.97)	(1.30)
LTR	0.29**	0.00	0.04
	(2.33)	(0.07)	(0.77)
SVAR	-2.86	-1.70	-0.52
	(-0.83)	(-0.81)	(-0.34)
DP	2.35	1.37	0.33
	(0.70)	(0.70)	(0.24)
DY	-0.15	-0.19*	-0.13
	(-1.08)	(-1.88)	(-1.46)
EP	0.37***	0.30***	0.12**
	(2.67)	(2.95)	(2.22)
TMS	-0.05	-0.07	-0.03
	(-0.33)	(-0.61)	(-0.27)
DFY	0.03	-0.10	-0.00
	(0.13)	(-0.61)	(-0.00)
MKTRF	-0.42	-0.35	-0.08
	(-0.48)	(-0.61)	(-0.19)
Adj.R^2	17.02	30.89	42.29

Table 5
Model Comparison

This table compares the out-of-sample predictability of three methods: Principal Component Analysis (PCA), Forecast Combination (FC), and Partial Least Squares (PLS). We report the out-of-sample R-squares across various corporate bond portfolios, as defined in Table 2. Panel A (B) presents results when the forecasting horizon is 1 month (3 months). The entire sample period spans from July 2002 to December 2022, with the forecast evaluation period starting in July 2012.

Panel A: Model Comparison when $h = 1$						
		All	>=AA	A	BBB	<BBB
All	PCA	1.70	0.66	1.21	1.31	3.52
	FC	2.46	1.42	2.26	2.15	2.78
	PLS	7.28	3.44	5.81	6.56	8.33
Short	PCA	4.62	2.45	4.24	3.87	6.03
	FC	4.72	3.45	5.48	4.14	3.81
	PLS	13.14	9.19	13.30	11.84	9.96
Medium	PCA	2.58	1.39	1.94	1.77	3.03
	FC	3.05	1.82	2.88	2.58	2.45
	PLS	9.07	5.00	7.51	7.72	7.08
Long	PCA	0.57	0.49	0.52	0.49	0.95
	FC	1.37	0.96	1.33	1.30	1.74
	PLS	3.71	1.27	2.94	3.83	6.29
Panel B: Model Comparison when $h = 3$						
		All	>=AA	A	BBB	<BBB
All	PCA	3.46	0.80	2.02	2.72	10.86
	FC	5.32	1.73	3.89	5.00	9.93
	PLS	14.67	3.34	9.02	13.77	26.02
Short	PCA	10.28	3.27	6.90	9.27	18.16
	FC	11.97	5.60	10.90	11.80	13.00
	PLS	29.76	13.92	22.99	28.71	28.90
Medium	PCA	5.63	1.84	3.13	3.75	9.82
	FC	7.24	2.28	5.08	6.35	9.42
	PLS	19.36	3.36	11.42	16.63	24.35
Long	PCA	0.99	0.96	0.94	0.86	2.75
	FC	2.39	0.95	1.97	2.57	5.49
	PLS	6.38	-2.25	3.64	7.43	18.99

Table 6
Asset Allocation Implications

This table presents the annualized certainty equivalent return gains (CER gain) and Sharpe ratios (S_a^M) if mean-variance investors allocate assets between the corporate bond portfolios and risk-free bills using out-of-sample predictions based on the PLS default risk measure over the forecasting horizon h, where $h = 1$. For comparison, we also present the annualized Sharpe ratios if investors allocate their assets using the out-of-sample predictions based on prevailing means (S_a^B). We consider two different scenarios. Panel A (B) reports the implications of asset allocation for an investor with a relative risk-aversion coefficient γ of 3 (5), who can take a leverage up to a maximum of 4 (2) times. The sample period is from July 2002 to December 2022, and the out-of-sample period starts from July 2012.

Panel A: Max leverage = 4, $\gamma = 3$						
		All	>=AA	A	BBB	<BBB
All	CER gain	7.43	8.24	8.56	8.00	4.09
	S_a^B	0.30	0.10	0.16	0.27	0.60
	S_a^M	0.59	0.42	0.48	0.53	0.71
Short	CER gain	2.26	3.43	3.17	3.20	-0.38
	S_a^B	0.43	0.04	0.21	0.34	0.75
	S_a^M	0.64	0.44	0.58	0.60	0.74
Medium	CER gain	5.73	6.41	6.33	6.19	5.38
	S_a^B	0.37	0.16	0.25	0.31	0.49
	S_a^M	0.62	0.48	0.55	0.53	0.61
Long	CER gain	10.01	8.76	8.87	8.99	9.47
	S_a^B	0.25	0.13	0.18	0.26	0.55
	S_a^M	0.50	0.37	0.43	0.51	0.78
Panel B: Max leverage = 2, $\gamma = 5$						
		All	>=AA	A	BBB	<BBB
All	CER gain	3.28	3.58	3.68	3.60	1.38
	S_a^B	0.31	0.10	0.17	0.28	0.63
	S_a^M	0.58	0.39	0.46	0.53	0.72
Short	CER gain	1.04	1.58	1.49	1.55	-0.26
	S_a^B	0.43	0.04	0.21	0.34	0.75
	S_a^M	0.63	0.41	0.56	0.60	0.74
Medium	CER gain	2.64	2.99	2.93	2.79	1.77
	S_a^B	0.37	0.16	0.25	0.31	0.54
	S_a^M	0.63	0.48	0.55	0.54	0.62
Long	CER gain	5.60	5.17	5.48	5.09	5.19
	S_a^B	0.22	0.11	0.14	0.26	0.58
	S_a^M	0.47	0.36	0.42	0.48	0.79

Table 7
Out-of-Sample Predictability for Different Corporate Bond Portfolio Returns

This table presents the out-of-sample predictability of the PLS default risk measure when individual default risk measures are aggregated from firms with different credit ratings. We report the R^2_{OS} and the corresponding t-statistics obtained from the Clark and West (2007) tests. $\mathrm{D}^{\mathrm{PLS}}_{IG}$ refers to the PLS default risk measure when individual default risk measures are aggregated across firms with S&P credit ratings of at least BBB, while $\mathrm{D}^{\mathrm{PLS}}_{HY}$ represents the PLS default risk measure when individual default risk measures are aggregated across firms with credit ratings lower than BBB. The sample period spans from July 2002 to December 2022, with the out-of-sample period starting from July 2012.

Panel A: Out-of-Sample Predictability of $\mathrm{D}^{\mathrm{PLS}}_{IG}$						
		All	>=AA	A	BBB	<BBB
All	R^2_{OS}	5.87	1.74	4.46	4.88	5.48
	t-stats	1.83	1.15	1.67	1.77	2.67
Short	R^2_{OS}	12.60	7.78	12.46	11.22	9.01
	t-stats	3.17	2.30	3.05	3.09	3.59
Medium	R^2_{OS}	6.86	1.37	5.48	4.97	3.32
	t-stats	2.20	1.26	1.98	2.05	2.41
Long	R^2_{OS}	1.98	-0.22	1.30	1.75	1.50
	t-stats	1.25	0.92	1.21	1.25	1.62
Panel B: Out-of-Sample Predictability of $\mathrm{D}^{\mathrm{PLS}}_{HY}$						
		All	>=AA	A	BBB	<BBB
All	R^2_{OS}	17.03	16.02	18.02	15.21	7.94
	t-stats	2.83	2.62	2.84	2.80	2.71
Short	R^2_{OS}	19.73	20.96	24.76	17.73	7.52
	t-stats	3.24	2.91	3.19	3.21	3.01
Medium	R^2_{OS}	16.68	16.18	18.71	15.18	7.06
	t-stats	2.88	2.65	2.89	2.81	2.56
Long	R^2_{OS}	14.10	12.99	14.31	13.14	8.39
	t-stats	2.69	2.55	2.77	2.66	2.52

Table 8
Predictability of PLS Default Risk Index on Macroeconomic Indicators

This table reports the in-sample predictability of the PLS default risk measure for six macroeconomic indicators: the Chicago Fed National Activity Index (CFNAI), the Smooth Recession Probability (SRP), Aruoba et al. (2009) Business Conditions Index (ADSI), unemployment rate (UR), the CBOE Volatility Index (VIX), and the Industrial Production Index (IPI). The whole sample period is from July 2002 to December 2022.

	h = 1			h = 3		
	beta	NW-t	Adj.R2	beta	NW-t	Adj.R2
CFNAI	-0.17	-2.05	2.37	-0.24	-2.26	5.44
SRP	0.43	3.58	18.42	0.41	2.54	16.09
ADSI	-0.19	-2.13	3.39	-0.19	-2.13	3.29
UR	0.43	6.37	17.76	0.47	6.14	22.07
VIX	0.49	5.39	23.98	0.47	3.64	21.36
INDPRO	-0.43	-5.57	18.57	-0.46	-4.35	20.79

Appendix for Aggregated Default Risk and Corporate Bond Returns

Variable Definition

WCAPAT	Working capital to assets ratio.
REAT	Retained earnings to assets ratio
EBITAT	Earnings before interest and tax to assets ratio.
MELT	Market value of equity to liabilities ratio.
SALEAT	Sales to assets ratio.
SIZE	Adjusted firm size. SIZE is measured as log(AT/GNPDEF), where AT is the total assets, and GNPDEF is the Gross National Product Implicit Price Deflator with base value of 100 for 2017.
LTAT	Liabilities to assets ratio.
LCTACT	Current liabilities to current assets ratio.
OENEG	1 if the total liabilities exceeds the total assets, 0 otherwise.
NIAT	Net income to assets ratio.
FUTL	Cash flow from operations to liabilities ratio.
INTWO	1 if the net income has been negative for the past two consecutive years; otherwise, it equals 0.
CHIN	The change of net income as defined in Ohlson (1980). CHIN is calculated as NI_t^* - NI_{t-1}^* / $\lvert\mathrm{NI}_t^* + \mathrm{NI}_{t-1}^*\rvert$, where NI_t^* (NI_{t-1}^*) is the net income of year t ($t-1$).
MB	Market-to-book ratio.
CASHAT	Cash to assets ratio.
RSIZE	Relative size of a given firm, measured as the log ratio of its market capitalization to that of the S&P 500 index.
EXRET	The monthly log excess return of each firm relative to the S&P 500 index.

SIGMA	The standard deviation of each firm's daily stock return for the past 3 months.
PRICE	The log price of each firm. The price is truncated above at \$15.
HHDP	Default probability as defined in Hannan and Hanweck (1988).
DD	Distance to default as calculated in Bharath and Shumway (2008).
RATING	Number ratings as in Avramov et al. (2009). The entire mapping between letter ratings and number ratings is as follows: $AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11, BB = 12, BB- = 13, B+ = 14, B = 15, B- = 16, CCC+ = 17, CCC = 18, CCC- = 19, CC = 20, C = 21, D = 22$.
CWDP	The risk-neutral default probability as in Carr and Wu (2011).

Table A1
Summary Statistics for Returns of Corporate Bond Portfolios

This table presents the summary statistics of the returns for different corporate bond portfolios, including the mean, standard deviation, 25th percentile, median, 75th percentile, skewness, and first-order autocorrelation. We classify corporate bonds into four groups by their ratings: higher than AA (>=AA), A, BBB, and lower than BBB (<BBB). We classify corporate bonds into three groups by their maturities: Short, Medium, and Long includes corporate bonds mature less than 3 years, 4-10 years, and longer than 10 years, respectively. The row labeled ">=AA, ALL" provides the summary statistics for the corporate bond portfolio that includes all bonds with credit ratings of at least AA across all maturities, and similar labels are used for other classifications. The sample period is from July 2002 to December 2022.

	Mean	STD	25% Pctl	Median	75% Pctl	Skew	$\rho(1)$
All, All	0.50	1.88	-0.34	0.59	1.32	-0.26	0.15
All, Short	0.40	1.06	-0.08	0.42	0.88	-0.27	0.18
All, Medium	0.52	1.84	-0.27	0.64	1.38	-0.47	0.16
All, Long	0.59	2.99	-0.89	0.79	2.03	-0.01	0.12
>=AA, All	0.35	1.73	-0.44	0.40	1.18	-0.16	0.10
>=AA, Short	0.26	0.88	-0.14	0.25	0.63	-0.49	0.10
>=AA, Medium	0.38	1.71	-0.45	0.45	1.27	-0.32	0.12
>=AA, Long	0.50	3.04	-0.88	0.53	2.06	0.15	0.07
A, All	0.41	1.88	-0.44	0.49	1.28	0.10	0.13
A, Short	0.31	0.98	-0.17	0.30	0.80	-0.28	0.17
A, Medium	0.43	1.78	-0.41	0.51	1.30	-0.05	0.14
A, Long	0.51	3.03	-1.11	0.66	2.17	0.34	0.11
BBB, All	0.50	2.02	-0.48	0.59	1.42	-0.70	0.15
BBB, Short	0.39	1.10	-0.11	0.40	0.85	-0.58	0.18
BBB, Medium	0.50	1.94	-0.30	0.57	1.40	-1.09	0.17
BBB, Long	0.60	3.10	-0.90	0.74	2.06	-0.38	0.13
<BBB, All	0.81	2.59	-0.30	0.79	1.92	-0.58	0.14
<BBB, Short	0.78	2.15	-0.11	0.73	1.68	0.02	0.17
<BBB, Medium	0.79	2.76	-0.44	0.78	1.93	-0.83	0.11
<BBB, Long	1.00	3.64	-0.87	1.13	2.62	-0.72	0.14

Table A2
Pearson Correlation Matrix

This table reports the Pearson correlation matrix among the 23 aggregate default risk measures. All variables are detrended and standardized to have zero mean and unit variance. The sample period is from July 2002 to December 2022.

	WCAPAT	REAT	EBITAT	MELT	SALEAT	SIZE	LTAT	LCTACT	OENEG	NIAT	FUTL	INTWO
WCAPAT	1.00	-0.24	-0.13	0.40	0.09	-0.57	0.31	0.90	0.38	-0.20	0.02	0.07
REAT	-0.24	1.00	0.33	-0.83	-0.61	-0.26	0.57	-0.02	0.45	0.23	0.10	0.70
EBITAT	-0.13	0.33	1.00	-0.12	-0.74	-0.01	0.61	0.00	0.34	0.81	0.56	0.27
MELT	0.40	-0.83	-0.12	1.00	0.43	0.25	-0.37	0.14	-0.21	-0.08	-0.01	-0.55
SALEAT	0.09	-0.61	-0.74	0.43	1.00	0.36	-0.75	-0.09	-0.50	-0.64	-0.61	-0.64
SIZE	-0.57	-0.26	-0.01	0.25	0.36	1.00	-0.63	-0.68	-0.53	-0.02	-0.08	-0.34
LTAT	0.31	0.57	0.61	-0.37	-0.75	-0.63	1.00	0.54	0.66	0.58	0.34	0.58
LCTACT	0.90	-0.02	0.00	0.14	-0.09	-0.68	0.54	1.00	0.56	-0.08	0.07	0.14
OENEG	0.38	0.45	0.34	-0.21	-0.50	-0.53	0.66	0.56	1.00	0.20	0.15	0.36
NIAT	-0.20	0.23	0.81	-0.08	-0.64	-0.02	0.58	-0.08	0.20	1.00	0.32	0.36
FUTL	0.02	0.10	0.56	-0.01	-0.61	-0.08	0.34	0.07	0.15	0.32	1.00	0.23
INTWO	0.07	0.70	0.27	-0.55	-0.64	-0.34	0.58	0.14	0.36	0.36	0.23	1.00
CHIN	0.04	-0.24	0.44	0.22	-0.08	0.09	0.05	-0.01	-0.17	0.50	0.20	-0.09
MB	-0.01	0.77	-0.02	-0.84	-0.40	-0.55	0.50	0.17	0.38	0.03	-0.06	0.67
CASHAT	0.77	-0.66	-0.23	0.76	0.31	-0.14	-0.12	0.55	-0.02	-0.29	0.08	-0.28
RSIZE	-0.16	0.30	-0.40	-0.31	0.06	0.14	-0.19	-0.24	-0.18	-0.39	-0.19	0.27
EXRET	-0.16	0.02	-0.05	-0.05	-0.06	0.03	-0.02	-0.16	-0.12	-0.03	0.01	0.05
SIGMA	0.45	-0.15	-0.24	0.11	0.27	-0.35	-0.03	0.42	0.14	-0.19	-0.14	-0.03
PRICE	-0.29	0.41	0.19	-0.43	-0.35	-0.07	0.30	-0.10	0.05	0.05	0.17	0.10
HHDP	-0.12	0.56	-0.21	-0.49	-0.14	-0.17	-0.05	-0.12	0.19	-0.30	-0.18	0.42
DD	0.60	0.19	-0.16	-0.12	-0.02	-0.52	0.41	0.73	0.37	-0.24	-0.01	0.17
RATING	-0.55	-0.10	-0.18	0.12	0.38	0.76	-0.62	-0.66	-0.56	-0.26	-0.18	-0.41
CWDP	0.47	-0.30	-0.27	0.20	0.30	-0.29	-0.07	0.40	-0.01	-0.17	-0.16	-0.06

	CHIN	MB	CASHAT	RSIZE	EXRET	SIGMA	PRICE	HHDP	DD	RATING	CWDP
WCAPAT	0.04	-0.01	0.77	-0.16	-0.16	0.45	-0.29	-0.12	0.60	-0.55	0.47
REAT	-0.24	0.77	-0.66	0.30	0.02	-0.15	0.41	0.56	0.19	-0.10	-0.30
EBITAT	0.44	-0.02	-0.23	-0.40	-0.05	-0.24	0.19	-0.21	-0.16	-0.18	-0.27
MELT	0.22	-0.84	0.76	-0.31	-0.05	0.11	-0.43	-0.49	-0.12	0.12	0.20
SALEAT	-0.08	-0.40	0.31	0.06	-0.06	0.27	-0.35	-0.14	-0.02	0.38	0.30
SIZE	0.09	-0.55	-0.14	0.14	0.03	-0.35	-0.07	-0.17	-0.52	0.76	-0.29
LTAT	0.05	0.50	-0.12	-0.19	-0.02	-0.03	0.30	-0.05	0.41	-0.62	-0.07
LCTACT	-0.01	0.17	0.55	-0.24	-0.16	0.42	-0.10	-0.12	0.73	-0.66	0.40
OENEG	-0.17	0.38	-0.02	-0.18	-0.12	0.14	0.05	0.19	0.37	-0.56	-0.01
NIAT	0.50	0.03	-0.29	-0.39	-0.03	-0.19	0.05	-0.30	-0.24	-0.26	-0.17
FUTL	0.20	-0.06	0.08	-0.19	0.01	-0.14	0.17	-0.18	-0.01	-0.18	-0.16
INTWO	-0.09	0.67	-0.28	0.27	0.05	-0.03	0.10	0.42	0.17	-0.41	-0.06
CHIN	1.00	-0.21	0.06	-0.43	-0.19	0.22	-0.32	-0.33	-0.04	-0.08	0.25
MB	-0.21	1.00	-0.52	0.33	0.02	0.17	0.17	0.49	0.37	-0.42	0.09
CASHAT	0.06	-0.52	1.00	-0.08	-0.03	0.18	-0.21	-0.32	0.23	-0.20	0.26
RSIZE	-0.43	0.33	-0.08	1.00	0.27	-0.37	0.36	0.56	0.05	0.34	-0.35
EXRET	-0.19	0.02	-0.03	0.27	1.00	-0.35	0.24	0.07	-0.11	0.09	-0.28
SIGMA	0.22	0.17	0.18	-0.37	-0.35	1.00	-0.62	-0.06	0.30	-0.43	0.84
PRICE	-0.32	0.17	-0.21	0.36	0.24	-0.62	1.00	0.16	0.04	0.18	-0.64
HHDP	-0.33	0.49	-0.32	0.56	0.07	-0.06	0.16	1.00	0.07	0.07	-0.21
DD	-0.04	0.37	0.23	0.05	-0.11	0.30	0.04	0.07	1.00	-0.34	0.31
RATING	-0.08	-0.42	-0.20	0.34	0.09	-0.43	0.18	0.07	-0.34	1.00	-0.41
CWDP	0.25	0.09	0.26	-0.35	-0.28	0.84	-0.64	-0.21	0.31	-0.41	1.00

Table A3
Trend Test for Default Risk Measures

This table shows the coefficients for the 23 aggregate default risk measures obtained from the following regression:

$$D_{i,t} = \alpha_i + \beta\, t + u_{i,t} \quad \text{for} \quad t = 0, ..., T$$

where $D_{i,t}$ is the i^th aggregate default risk measure, t represents a month indicator, which starts at 0 at the beginning of the sample period, and $\hat{u}_{i,t}$ is the detrended value of the i^th aggregate default risk measure. $\hat{\beta}$ are multiplied by 10^4 for presentation. The sample period is from July 2002 to December 2022. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$\hat{\beta}$	t-stats
WCAPAT	0.82***	7.11
REAT	-1.15***	-4.73
EBITAT	0.02	0.70
MELT	-78.36***	-7.45
SALEAT	-1.53***	-15.69
SIZE	-30.06***	-57.10
LTAT	3.09***	17.56
LCTACT	1.52***	4.64
OENEG	1.59***	31.69
NIAT	-0.99***	-9.44
FUTL	0.76***	9.84
INTWO	1.84***	11.88
CHIN	0.23	0.29
MB	299.95***	20.12
CASHAT	-2.19***	-19.59
RSIZE	-9.84***	-23.19
EXRET	0.09**	2.16
SIGMA	-0.18	-0.17
PRICE	1.62***	13.16
HHDP	0.37***	8.03
DD	-3.41***	-11.68
RATING	29.51***	14.67
CWDP	-1.02***	-3.86

Table A4
In-Sample Predictability of Individual Default Risk Measures

This table reports the results of the following predictive regression:

$$r_{t,t+h} = \alpha + \beta \times D_{i,t} + \epsilon_{t,t+h}$$

where r_{t+h} is the average excess returns of corporate bond portfolios including all corporate bonds in our sample over the forecasting horizon h, where $h = 1$ and 3 months. $D_{i,t}$ the i^{th} aggregate default risk measure at month t. All individual default risk measures are detrended and standardized to have zero mean and unit variance. The sample period is from July 2002 to December 2022. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$h = 1$			$h = 3$		
	$\hat{\beta}$	t-stats	Adj.R^2	$\hat{\beta}$	t-stats	Adj.R^2
WCAPAT	0.17	1.01	0.50	0.17	1.42	1.85
REAT	-0.29	-2.20	2.18	-0.29	-2.89	5.98
EBITAT	0.13	0.80	0.08	0.12	0.85	0.74
MELT	0.41	3.33	4.68	0.42	3.90	13.05
SALEAT	0.10	0.62	-0.11	0.09	0.65	0.24
SIZE	-0.03	-0.24	-0.38	0.02	0.13	-0.39
LTAT	0.01	0.05	-0.41	-0.02	-0.21	-0.38
LCTACT	0.16	1.06	0.33	0.14	1.30	1.10
OENEG	0.12	0.95	0.02	0.06	0.66	-0.09
NIAT	0.19	1.32	0.72	0.16	1.29	1.67
FUTL	-0.06	-0.65	-0.28	-0.04	-0.38	-0.27
INTWO	-0.15	-0.95	0.23	-0.14	-1.23	1.21
CHIN	0.34	2.83	3.18	0.32	2.74	7.51
MB	-0.27	-2.22	1.80	-0.29	-2.23	6.04
CASHAT	0.19	1.26	0.67	0.19	1.83	2.53
RSIZE	-0.56	-3.49	9.25	-0.45	-3.85	15.32
EXRET	0.05	0.39	-0.34	-0.05	-0.46	-0.21
SIGMA	0.47	2.52	6.26	0.38	3.92	10.85
PRICE	-0.50	-3.08	7.04	-0.48	-5.99	17.22
HHDP	-0.20	-1.25	0.74	-0.22	-1.90	3.33
DD	-0.03	-0.26	-0.37	-0.02	-0.15	-0.39
RATING	-0.25	-1.88	1.53	-0.21	-2.11	3.02
CWDP	0.33	1.68	2.95	0.36	3.32	9.61

Table A5
Out-of-Sample Predictability of Individual Default Risk Measures

This table reports the maximum out-of-sample R^2 (R^2_{OS}) for corporate bond portfolios as defined in Table 2. Specifically, for each corporate bond portfolio, we calculate the R^2_{OS} for all individual default risk measures and present the highest value obtained. Panel A (B) presents results when the forecasting horizon is 1 month (3 months). The sample period spans from July 2002 to December 2022, with the out-of-sample test beginning in July 2012. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Out-of-Sample Predictability of Individual Default Risk Measures when $h = 1$						
		All	>=AA	A	BBB	<BBB
All	R^2_{OS}	4.78**	4.91*	4.97**	3.73**	4.41**
	t-stats	1.89	1.43	1.69	1.87	2.01
Short	R^2_{OS}	6.40**	7.31**	6.65**	5.61**	4.55**
	t-stats	1.99	1.82	1.73	1.93	2.22
Medium	R^2_{OS}	4.26*	4.75*	4.65**	3.72*	3.97
	t-stats	1.61	1.59	1.80	1.53	1.27
Long	R^2_{OS}	3.69**	3.26*	3.24*	3.55**	4.49
	t-stats	1.69	1.35	1.55	1.75	1.25
Panel B: Out-of-Sample Predictability of Individual Default Risk Measures when $h = 3$						
		All	>=AA	A	BBB	<BBB
All	R^2_{OS}	9.86**	6.19**	8.14*	8.93*	15.13**
	t-stats	1.80	1.82	1.55	1.43	2.20
Short	R^2_{OS}	16.25**	12.20**	13.81*	14.85**	15.25***
	t-stats	1.81	1.67	1.54	1.73	2.45
Medium	R^2_{OS}	10.88*	6.30*	8.27*	9.41*	14.25**
	t-stats	1.53	1.40	1.64	1.43	2.12
Long	R^2_{OS}	7.54*	4.31**	5.82*	7.66**	11.37**
	t-stats	1.60	1.70	1.41	1.70	1.87