International Corporate Bond Market: Uncovering Risks Using Machine Learning[*]

Delong Li
Gordon S. Lang School of Business and Economics
University of Guelph
delong@uoguelph.ca

Lei Lu
Asper School of Business
University of Manitoba
lei.lu@umanitoba.ca

Zhen Qi
Asper School of Business
University of Manitoba
qiz1@myumanitoba.ca

Guofu Zhou
Olin Business School
Washington University in St. Louis
zhou@wustl.edu

This draft: June 18, 2022

Abstract

In this paper, we explore what factors drive expected corporate bond returns all over the world. With a novel dataset, and utilizing machine learning models, we find there is strong predictability of corporate bond returns in international markets. However, the documented factors that drive bonds in the U.S. and non-U.S. developed markets are substantially different from factors that impact bonds in the emerging markets, where inflation, downside risk, duration, illiquidity, and volatility are more influential. Moreover, U.S.-based equity and bond factors do not contribute predictive power to non-U.S. corporate bonds, indicating that international corporate bond markets are not well integrated.

***JEL Classifications*:** C52, G10, G11, G15
***Keywords*:** corporate bonds; international asset pricing; machine learning; return predictability

[*] We are grateful for valuable comments from

1. Introduction

This paper provides the first study on the cross-sectional predictability of corporate bond returns in international markets with machine learning techniques. Earlier work, in contrast, solely focuses on the U.S. market (Fama and French, 1993; Bai, Bali, and Wen, 2019; He, Feng, Wang and Wu 2021; Huang and Shi, 2021; Bali, Goyal, Huang, Jiang and Wen, 2022). We find strong evidence of international bond predictability and that non-U.S. corporate bonds, especially those issued by firms in emerging markets, are substantially different from U.S. corporate bonds in terms of return predictors. For example, inflation, downside risk, duration, illiquidity, and volatility are more important in non-U.S. markets than in the U.S. market. Moreover, U.S.-based asset pricing factors do not provide additional predictive power to returns of non-U.S. bonds. These results shed light on that international corporate bond markets are not well integrated, and thus, bond investors need to carefully account for local economic risks.

There has been a lack of research in this area primarily because data of international corporate bonds are scarce. Only since recently, have researchers started investigating bond securities outside of the U.S. (Bekaert and De Santis, 2021; Li, Magud, and Werner, 2021). Presumably, the non-U.S. bond markets, particularly emerging markets, can be fundamentally different from the U.S. market, given more incomplete information, less investor protection, and lower financial stability. It is of critical importance for researchers and policymakers to understand how these markets differ from the U.S. and what determine their unique bond prices. This work is also of interests to practitioners, given that large asset management companies have started offering investment vehicles with exposure to international corporate bonds.

Our paper utilizes a proprietary data from IHS Markit, including high-quality pricing information for a large set of international corporate bonds. We match this data with Bloomberg and Datastream to obtain a unique dataset of approximately 13,000 corporate bonds issued by companies in 73 countries, for which we can observe bond returns (based on transactions or quotations), bond characteristics, stock pricing and characteristics (if existed), and macroeconomic fundamentals.[1] The bond characteristics include (i) bond fundamental characteristics (i.e., age, illiquidity, and credit rating); (ii) return-based characteristics (i.e., short-term reversal, momentum and volatility); and (iii) exposures to some factors (i.e., MKT, SMB, HML, TERM, and DEF in Fama and French (1993)). The macro variables include exchange rate growth, GDP growth, inflation, geopolitical risk, economic policy uncertainty and world uncertainty. To the best of our knowledge, this is the largest and most comprehensive international data of corporate bonds ever examined in the literature.

We apply cutting-edge machine learning techniques to our dataset to study the cross-sectional predictability of corporate bond returns. Importantly, we aim to distinguish the predictability outside of the U.S. from that within U.S. We consider mainly 20 bond characteristics and 6 macroeconomic variables. We first categorize global corporate bond markets into three markets: U.S., non-U.S. developed, and emerging markets. Then, we follow Gu, Kelly, and Xiu (2020) to use various machine learning methods, including penalty estimation, dimension reduction approaches, regression tree models, and neural network based methods, to predict weekly bond returns, and compare the models' performance with that of the ordinary least squares (OLS).

We find that OLS fails to produce significant out-of-sample forecasting power for expected corporate bond returns in all markets, usually yielding a negative out-of-sample *R*-squared.

[1] The IHS Markit database has been employed to obtain information on corporate bond illiquidity (Friewald, Jankowitsch and Subrahmanyam 2012; Schestag, Schuster and Uhrig-Homburg 2016). For more information on the differences in commonly used corporate bond databases refer to Huang and Shi (2021).

However, all the machine learning models can greatly improve the predictive power and generate reasonable, positive R-squared both within and outside of the U.S. market. We further show that the improvement of the predictive power mainly comes from investment-grade bonds. The best machine learning models for non-U.S. bond markets are based on regression trees (for developed economies) and neural networks (for emerging markets).

In portfolio analysis, we find that all the machine learning models, when being applied to the U.S. market, can generate both economically and statistically significant excess returns, ranging between 8.84 to 11.44 percent per year, and an annualized Sharpe ratio varying from 1.40 to 1.86, from a long-short portfolio strategy. However, the OLS can only deliver annualized excess returns of around 7.28 percent and Sharpe ratio of 1.03. We find similar patterns for corporate bonds outside of the U.S., but the performance of OLS is much worse in emerging markets with annualized excess return of -2.08 percent and annualized Sharpe ratio of -0.33, respectively. However, machine learning models still generate positive annualized Sharpe ratio ranging from 1.05 to 1.71.

In addition, we find evidence that in different groups of countries, bond returns are determined by distinct characteristics and factors. Consistent with He et al. (2021) and Bali et al. (2022), our results indicate that short-term reversal and co-skewness are the most important drivers of corporate bond returns in U.S. Bond short-term reversal is also identified as a crucial predicting characteristic in non-U.S. developed markets, however, we find that momentum and duration are more influential outside of the U.S. Moreover, in emerging markets, half of the ten most important determinants for corporate bond returns are macroeconomic variables, including inflation, uncertainty, geopolitical risk, exchange rate growth and GDP growth, but this phenomenon does not hold for U.S. or other developed economies. Among the macro variables, inflation is the most important factor. Other crucial characteristics that drive bond returns in emerging markets, but less so in U.S., include downside risk, duration, illiquidity, and volatility.

The differential reliance on characteristics and factors of bond pricing suggests that international bond markets might not be integrated. To test for this hypothesis, we consider training our machine learning models with U.S. data to predict returns in the other two markets. Results show that in emerging economies, the U.S. trained models substantially underperform models trained by local data, both economically and statistically, for most of the machine learning models we consider. But in developed economies other than U.S., the U.S. trained models perform as well as models trained by local data. These results indicate that compared with other developed economies, emerging markets is much less integrated with U.S.

To further illustrate the lack of cross-market integration of corporate bonds, we include exposure to U.S. equity and bond factors (MKT, SMB, HML, DEF and excess bond market return) as new characteristics for non-U.S. corporate bonds. We aim to examine whether the inclusion of such U.S. exposure can improve the performance of machine learning models to predict bond returns outside of the U.S. Results show that there is no significant difference in predicting performance between models with or without U.S. exposure, reinforcing our argument that international corporate bond markets may not be well integrated.

Last, we investigate whether stock characteristics can help improve cross-sectional return predictability of corporate bonds. We further introduce 21 stock characteristics to our model, following Gu et al. (2020) and He et al. (2021), in addition to the existing bond and macro predictors. We find similar mixed results in all three markets. Most of machine learning models show no significant difference in predicting performance between models with and without stock characteristics. The predicting performance of several models even decreases after including stock predictors. This result indicates that bond and macro variables play major roles in predicting future corporate bond returns in all of these three markets.

This paper contributes to three strands of literature. First, our paper adds to the growing literature on predictability of corporate bond returns. The existing literature studies many bond characteristics including default and term betas (Fama and French, 1993; Gebhardt, Hvidkjaer, and Swaminathan, 2005), momentum (Jostova, Nikolova, Philipov, and Stahel, 2013), liquidity (Lin, Wang, and Wu, 2011; Bongaerts, De Jong, and Driessen, 2017), downside risk and short-term reversal (Bai et al., 2019), volatility (Bai et al., 2019; Chung, Wang and Wu, 2019; Bao, Chen, Hou and Lu, 2021), bond book-to-market ratio (Bartram, Grinblatt, and Nozawa, 2020), long-run consumption growth (Elkamhi, Jo, and Nozawa, 2021) and long-term reversal (Bali, Subrahmanyam, and Wen, 2021). However, all of these studies focus on the U.S. market. Few papers study international corporate bond markets. Internationally, Valenzuela (2016) documents that market liquidity contributes to credit spreads and Lee, Rizova, and Wang (2022) find that forward rates contain information about corporate bond returns. Bekaert and De Santis (2021) find that ratings, maturity and bond market beta are influential characteristics to explain corporate bond returns in major developed countries. In this paper, we use a novel data of international corporate bonds to conduct out-of-sample instead of in-sample tests. Goyal and Welch (2008) suggest that out-of-sample tests are the most rigorous evidence for return predictability. Additionally, we use machine learning techniques to deal with the concern of large number of variables.

Second, this paper extends and complements the burgeoning literature that predicts asset returns with machine learning. Several studies have shown that machine learning does well in improving predicting performance and identifying influential predictors in the stock market (Feng, Giglio, and Xiu, 2020; Freyberger, Neuhierl, and Weber, 2020; Gu et al., 2020; Kozak, Nagel, and

Santosh, 2020; and Giglio, Liao, and Xiu, 2021; Leippold, Wang, and Zhou, 2021; Dong, Li, Rapach, and Zhou, 2022; He, Huang, Li and Zhou, 2022). Bianchi, Büchner, and Tamoni (2021) find that non-linear machine learning models such as regression trees and neural network outperform linear techniques to predict U.S. Treasury bond returns. Several studies introduce machine learning methods to predict corporate bond returns in the U.S. market (Lin, Wu and Zhou, 2018; He et al., 2021; Bali et al., 2022). Different from these studies, we use machine models and study corporate bond return predictability in international markets and find significant differences in return predictors among U.S., non-U.S. developed, and emerging markets.

Last, our paper expands extant research on integration of international financial markets. There is a long debate on whether stocks are priced locally or globally. Most of these studies find that cross-sectional return can be better explained by local factors (Griffin, 2002; Bekaert, Hodrick, and Zhang, 2009; Hou, Karolyi, and Kho, 2011; Chaieb, Langlois, and Scaillet, 2021; Hollstein, 2022). However, to our knowledge, Bekaert and De Santis (2021) is the only one examining integration of international corporate bond markets. Our paper differs from their paper in two ways. First, they only investigate the integration across major developed countries, while we include a large number of emerging markets. Second, we include a vast of bond, macro and stock characteristics utilizing machine learning models.

2. Data and Methodology

2.1. Data

We obtain daily data on the pricing of corporate bonds from IHS Markit for the period from March 2016 to April 2019.[2] Unlike transaction-level data used in the U.S. (i.e., TRACE),

[2] We exclude data before 2016 since bond valuations in earlier data are based on matrix pricing techniques rather than dealer quotes.

transaction price is usually unavailable for corporate bonds outside of U.S. and the price of Markit dataset is generally based on dealers' quotes or asset pricing models such as matrix pricing. However, such prices have been viewed as fundamental valuation of bond prices (Schestag et al, 2016). In addition to bid, mid, and ask prices, Markit data also includes multiple types of yields, and a variety of bond simple features such as coupon, bond grades (IG or HY) and issuers, and bond features that may need complex calculations such as duration and option-adjusted spreads.

To obtain additional bond-level characteristics such as country of risk, equity international security identification number (ISIN), amount issued, and credit ratings, we link the Markit data to Bloomberg through each bond's ISIN. To identify the country of origin of a bond and bonds' market belong to, we use the country of risk as defined by Bloomberg.[3] To compare corporate bonds across countries, we further create three categorical groups of countries or markets that allow for a fair comparison of bonds: U.S. market, non-U.S. developed market, and emerging market.

[Insert Table 1 Here]

To filter the data, we (1) keep bonds denominated in U.S. dollars, (2) drop duplicated bonds issued with the same bond ticker from Bloomberg, (3) drop bonds with amount issued less than 10000 $, (4) drop bonds that are perpetual, inflation-adjusted, or defaulted, (5) drop bonds with maturity less than half a year, (6) drop bonds with midprice under $5 or above $1000, (7) drop bonds without rating, (8) drop bonds without equity ISIN, (9) keep only bonds with a fixed or zero coupon, and (10) winsorize raw bond return at the 2.5% and 97.5% levels to correct for potential data errors. Table 1 shows that our final sample includes 1,297,006 weekly observations for 13,219

[3] This approach takes into account the issuing company's country of domicile, country of listing, country of largest revenue, and reporting currency (most important to least important). See the documents provided by Bloomberg L.P. for more details.

U.S. dollar corporate bonds, issued by 1,999 companies.[4] U.S. market, non-U.S. developed markets, and emerging markets account for 77%, 13% and 10% observations, respectively.

Following Bai et al. (2019), the weekly bond return is calculated as:

$$r_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1\ , \tag{1}$$

where $P_{i,t}$ is midprice, $AI_{i,t}$ is accrued interest, and $C_{i,t}$ is coupon payment for bond i in week t. We denote $R_{i,t}$ as bond i's return in excess of U.S. risk-free rate in week t. Returns are calculated using the last available price observation of week t ($P_{i,t}$) and the last available price observation of week $t-1$ ($P_{i,t-1}$) to allow for non-trading days.

[Insert Table 2 Here]

Table 2 reports the time-series average of the cross-sectional bond return' distribution and characteristics. The average weekly bond return for U.S., non-U.S. developed, and emerging markets is 0.06 %, 0.05% and 0.07% respectively. Compare to U.S. market, non-U.S. developed market shows lower credit risk (*Rating* 7.30 vs. 8.42), but emerging market has higher credit risk (*Rating* 9.86 vs. 8.42). The U.S. market has the longest time to maturity and largest downside risk, while emerging market shows the highest illiquidity among these three markets. U.S. bond market has large trading volume and thus is more likely to have extreme returns.

Finally, we include 20 bond characteristics, 6 macro variables and 21 stock characteristics. Appendix A provides a detailed description of these 47 variables as well as data sources. We obtain stock pricing and trading information, and accounting variables from Datastream. We normalize all characteristics to zero mean and unit standard deviation by week for each of these three markets. For missing characteristics, we follow Bali et al. (2022) and Gu et al. (2020) to replace missing

[4] To estimate beta-related bond characteristics, we require at least 12 observations for each bond.

characteristics with the cross-sectional median value of these characteristics for each week.

2.2. Machine Learning Models

Following Bali et al. (2022) and Gu et al. (2020), we focus on five categories of machine learning models: OLS, penalized linear (LASSO, RIDGE and ENet), dimension reduction (PCR and PLS), regression trees (RF, GBRT), neural network (NN1, NN2 and NN3).[5] We separate our full sample period into three disjoint time periods: (1) the first year as training period, T_1, to estimate the model; (2) the second year as validation period, T_2, to tune the hyperparameters; (3) the rest three quarters as test period, T_3, for out-of-sample analysis and evaluation of the model's performance. Due to limited computational resources and some of our characteristics updated quarterly, we retrain models quarterly instead of weekly.

2.3. Out-of-sample Performance Evaluation

Following Bali et al. (2022) and Gu et al. (2020), we use the out-of-sample R-squared (R^2_{OOS}) to evaluate the predicting power of machine learning models for corporate bond returns:

$$R^2_{OOS} = 1 - \frac{\sum_{(i,t)\in T_3}(R_{i,t} - \hat{R}_{i,t})^2}{\sum_{(i,t)\in T_3}(R_{i,t})^2}, \tag{2}$$

Where $R_{i,t}$ denotes actual bond excess returns and $\hat{R}_{i,t}$ denotes one-week-ahead predictions of bond i in week t. This R^2_{OOS} measures the proportional reduction in mean squared forecast error relative to a naive forecast of zero benchmark, assuming that the one-week-ahead expected bond return equals risk-free rate.

To calculate the relative importance of different characteristics, we follow Gu et al. (2020)

[5] The detailed description of these methods and the choice of hyperparameter can be referred to Gu et al. (2020).

and first calculate the reduction of time-series average weekly R-squared ($\bar{R}^2_{OOS,t}$) from setting all values of a given predictor to zero while keep the remaining predictors unchanged. Variable importance is then defined as the relative reduction of $\bar{R}^2_{OOS}$. In this way, the variable importance of the characteristic with lowest R-squared reduction is assigned to 0, while the characteristic with highest R-squared reduction has variable importance of 1.

3. Empirical Results

3.1. Predictability of Bond Characteristics and Macro Variables

We first examine the predicting performance of machine learning models with 20 bond characteristics and 6 macro variables. Our main purpose is to verify whether the predicting performance based on Markit data in the international market is comparable to those in He et al. (2021) and Bali et al. (2022) which use transaction-level TRACE data for U.S. market.

[Insert Table 3 Here]

Table 3 reports the out-of-sample R-squared (R^2_{OOS}) for all models. Panel A of Table 3 presents R^2_{OOS} in the U.S. market. The first row reports R^2_{OOS} for all corporate bonds, and the second row and third row examine the predictive performance for investment-grade and non-investment-grade bonds separately. For the full sample in the U.S. market, we find that the OLS model produces an R^2_{OOS} of -2.67%, indicating that OLS's forecasting power is worse than a naive forecast of zero benchmark. This is consistent with the findings in both Bali et al. (2022) and He et al. (2021). However, the other columns of first row indicate that machine learning improves predicting performance of OLS for all machine leaning models and has positive R^2_{OOS} ranging from 1.94% (NN1) to 3.27% (NN3). Compared to R^2_{OOS} for all bonds, the results in the second row indicate that all machine learning models, except for NN1, have higher R^2_{OOS} and thus generate better predicting performance for investment-grade bonds. In contrast, all machine learning models, except for NN3, have negative R^2_{OOS}, ranging from -0.83% for LASSO and ENet to -0.18% for NN2, for non-investment-grade bonds (third row of Table 3), and OLS still has the lowest R^2_{OOS} (-2.30%). This result indicates that even machine learning models fail to deliver significant out-of-sample forecasting power for returns of non-investment-grade bonds. Consistent with He et al. (2021), we find better predictive performance for investment-grade bonds in the U.S. market.

Panel B and Panel C of Table 3 report R^2_{OOS} for non-U.S. market and emerging market respectively. Similar to the results of the U.S. market, we find that machine learning models perform better than OLS in terms of predicting performance and investment-grade bonds have better predicting power than non-investment-bond. Interestingly, we find that all machine learning models generate positive R^2_{OOS}, ranging from 2.21% for RF to 2.78% for NN3, for non-investment-grade bonds in the emerging market.

3.2. Portfolios Analysis

In addition to examining the predicting power of machine learning models for corporate bonds returns across markets, we further investigate the economic significance of machine learning models with portfolio analysis. Specifically, at the end of each week, we sort bonds in each of three markets into deciles based on the forecasts of bond returns for the next week, and then construct both value-weighted (amount issuance as weight) and equal-weighted long-short portfolios of corporate bonds. Table 4 presents value-weighted weekly portfolio performance for all bonds (including both investment-grade and non-investment-grade bonds). We report the average weekly return of decile 1 (“Low”) to decile 10 (“High”) and denote the long-short portfolio by “High-Low”. Annualized Sharpe ratio for long-short portfolios is also presented.

[Insert Table 4 Here]

Panel A of Table 4 reports the results in the U.S. market. We find that long-short portfolio strategy based on the forecasts of machine learning models generates economically and statistically significant return performance with average weekly return ranging from 0.17% to 0.22%. In contrast, the traditional OLS produces the smallest weekly return of 0.14% from the long-short portfolio strategy. Meanwhile, the results of annualized Sharpe ratios from the last column of panel A also indicate that machine learning models have better performance (i.e., higher Sharp ratio) than OLS. Among our ten machine learning models, LASSO and RIDGE are the top two best models, with the same weekly long-short portfolio average return of 0.22% (*t-stat*= 6.69 and 3.89) and Sharpe ratio of 1.86 and 1.82, respectively.

[Insert Table 5 Here]

We find similar results, i.e., machine learning having better long-short performance than OLS, in non-U.S. developed market and emerging market as shown in panel B and panel C of Table 4. However, OLS performs extremely bad in emerging market, with the weekly long-short portfolio average return of -0.04% (*t-stat*= -0.60) and Sharp ratio of -0.33. When we use equal-weighted portfolios, the results are qualitatively the same, which are shown in Table 5.

3.3. Characteristic Importance across Markets

We next identify bond characteristics and macro variables that are important to improve the predicting performance of machine learning models in each market. Specifically, following Gu et al. (2020), we first calculate the reduction of time-series average weekly *R*-squared ($\bar{R}^2_{OOS}$) from setting all values of a given predictor to zero, while keep the remaining predictors unchanged. Variable importance is defined as the relative reduction of $\bar{R}^2_{OOS}$. In this way, the variable importance of the characteristic with lowest *R*-squared reduction is assigned to 0, while the characteristic with highest *R*-squared reduction has variable importance of 1. To get the overall rankings of characteristics across models, we rank the importance of each characteristic for each model and then average them into a single rank. Figure 1 to Figure 3 present the overall rankings of characteristics across models for U.S., non-U.S. developed and emerging markets, respectively. Each column corresponds to a predictive model, and color gradients within each column indicate the most influential (dark blue) to the least influential (white) characteristics.

[Insert Figure 1 Here]

Figure 1 shows that bond short-term reversal (*REV_Bond*) is identified as the most influential predicting determinant by all machine learning models except for neural network models (i.e., NN1, NN2 and NN3) in the U.S.. This finding is consistent with Bai et al. (2019) and He et al. (2021). Although time to maturity (*MAT*), bearing the highest overall rank in Bali et al. (2022), fails to be picked out as one of the five most important characteristics, we do find that it is the fourth most important predictor in their paper. Co-skewness (*COSKEW*) is identified as the second most important predictor in our paper. We also find that some exposure measures to common factors, including *BETA_SMB*, *BETA_MKT*, *BETA_BMkt*, *BETA_TERM*, are among the ten most important characteristics.

[Insert Figure 2 Here]

Figure 2 presents the overall rankings of characteristics in non-U.S. developed market. Similar to the results in U.S., bond short-term reversal (*REV_Bond*) is also identified as the most important predicting characteristic for machine learning models. Moreover, factor exposure (*BETA_BMkt*) and age (*AGE*) are also among the ten most important predictors. However, we find that four-week momentum (*MOM4WBond*) and interest rate risk measured by duration (*DUR*) are the second and fourth most important predictors in non-U.S. developed market, while these two characteristics are ranked at the bottom in U.S. (Figure 1). Meanwhile, some macro variables such as exchange rate growth (*USExGrowth*) and geopolitical risk (*GPRChange*) play relatively important role in improving the predicting power of machine learning models.

[Insert Figure 3 Here]

Figure 3 reports variable importance in emerging market. Very different from the characteristic rankings in U.S. or non-U.S. markets, inflation (*CPIGrowth*) is the most important predicting characteristic in emerging market. The other four most important predictors in emerging market are downside risk (*VaR5*), duration (*DUR*), illiquidity (*ILLIQ_Bond*) and volatility (*VOL*). Another notable result is that half of the ten most important determinants are macro variables, including inflation (*CPIGrowth*), world uncertainty (WUIChange), geopolitical risk (*GPRChange*), exchange rate growth (*USExGrowth*) and GDP growth (*GDPGrowth*). Emerging market and U.S. market only share inflation (*CPIGrowth*) and illiquidity (*ILLIQ_Bond*) in their ten most important predictors, while duration (*DUR*), inflation (*CPIGrowth*), geopolitical risk (*GPRChange*), exchange rate growth (*USExGrowth*) and value factor exposure (*BETA_HML*) are all identified as among the top ten important predictors in both emerging and non-U.S. developed markets.

Overall, there are similarities in the return-characteristic relationship in U.S. and non-U.S. developed markets. For example, bond short-term reversal is the most important predicting characteristic in these two markets. However, this relationship is extremely different in U.S. and emerging markets, while emerging and non-U.S. developed markets share more similarities. Specifically, emerging and U.S. markets only share two of the most ten mort important predictors, and five predictors are the same for emerging and non-U.S. developed markets. In the emerging market, downside risk, interest rate risk, illiquidity and volatility play more significant role in improving the predicting performance of machine learning models. Moreover, macro variables, especially inflation and world uncertainty, are more important in emerging market.

3.4. Can U.S. Return-Characteristics Relationship be Applied to Other Markets?

In the above subsection, we find that U.S. market shares much more important predicting determinants with non-U.S. developed market compared to emerging market. To further compare such difference among these three markets, following Choi, Jiang and Zhang (2022), we investigate whether models based on the information of characteristics in the U.S. market generate better performance in predicting corporate bond returns in the non-U.S. developed and emerging markets, instead of using information of characteristics of their own market.[6] Specifically, we first estimate parameters and hyperparameters based on the training and validation sample in U.S., and then use these parameters and hyperparameters and predictor information of non-U.S. developed and emerging markets to estimate corporate returns in these two markets. To calculate the *t-stat*of difference between market-specific and U.S. models, we report time-series average weekly $\bar{R}^2_{OOS,t}$ rather than pooled R^2_{OOS} of equation (1).

[Insert Table 6 Here]

Panel A of Table 6 presents the results for non-U.S. developed market. The first row reports $\bar{R}^2_{OOS,t}$ based on market-specific model, and the second row shows the results using U.S. model. $\bar{R}^2_{OOS,t}$ difference and its *t-stat* are presented in the third and forth row, respectively. We find that most market-specific models fail to significantly outperform their U.S. comparisons. Even the predicting performance is better, i.e., negative $\bar{R}^2_{OOS,t}$ difference, for most of machine models when

[6] Since U.S. exchange rate growth (*USExGrowth*) is not applicable for U.S. market, it is not included to predict corporate bond returns for non-U.S. developed and merging markets.

using U.S. parameters and hyperparameters (i.e., LASSO, RIDGE, ENet, PCA, PLS and GBRT), the results are not significant as *t-stat* indicated. Among all machine learning models, we only find that market-specific neural network models (NN2 and NN3) significantly outperform their U.S. comparisons, with the difference of 8.18% (*t-stat*=4.03) and 17.45% (*t-stat*=17.45), respectively.

Panel B of Table 6 reports the results for emerging market. Quite different from the results in non-U.S. developed market, nine of eleven market-specific models significantly outperform their U.S. ones, with $\bar{R}^2_{OOS,t}$ difference varying from 1.90% (*t-stat*=2.81) for LASSO to 10.60% (*t-stat*=3.14) for NN3. Overall, the results of Table 6 indicate that emerging market is more different from U.S. market in terms of return-characteristics relationship than non-U.S. developed market.

3.5. Integration of International Bond Markets

In the above two sections, we find that U.S. bond market is more relevant to non-U.S. developed market rather than emerging market with regard to variable importance and return-characteristics relationship. In this subsection, we investigate cross-market integration for corporate bonds. In particular, we aim to examine whether information from U.S. market can improve the predicting performance for non-U.S. developed and emerging markets. In Figure 1, we show that bonds' exposures to Fama and French (1993)'s five factors (especially SMB, MKT and TERM) and bond market factor constructed based on our data are significantly important to improve predicting performance in the U.S. market. Thus, we include bonds' exposures to these 5 U.S. factors (excluding TERM) as new characteristics to test whether these predictors improve our predictions of corporate returns in non-U.S. developed and emerging markets.[7]

[Insert Table 7 Here]

[7] Due to a lack of information on returns of the long-term government bonds in non-U.S. markets, we have already applied U.S. TERM factor to construct *BETA_TERM* in both non-U.S. developed and emerging market.

The results from Panel A of Table 7 show that the predicting performance of OLS decrease once adding these five factor exposures with $\bar{R}^2_{OOS,t}$ difference of 0.41% (*t-stat*= 2.01). Half of our ten machine learning models i.e., LASSO, ENet, PCA, RF and GBRT) generate better predicting performance after adding the five U.S. factor exposures but none of them are significant. In contrast, we find a significant decrease of predictive power for RIDGE and NN1, with $\bar{R}^2_{OOS,t}$ difference of 0.13% (*t-stat*= 2.02) and 0.52 (*t-stat*= 2.02), respectively. Panel B of Table 7 reports the results for emerging market. Similarly, we find that the predicting performance of only half of our machine learning models (including LASSO, RIDGE, PLS, RF and NN1) improves when including U.S. factor exposures, but none of them are significant. Among the other half machine learning models, PCA, NN2 and NN3 has a significant decrease of predicting performance instead, with $\bar{R}^2_{OOS,t}$ difference ranging from 0.27% to 0.67%.

In general, the results in Table 7 show that information from U.S. market fails to significantly improve the predicting performance for non-U.S. developed and emerging markets. This result indicates that international corporate bond market is not well integrated.

3.6. Prediction Performance with Stock Characteristics

So far we only use bond characteristics and macro variables to predict corporate bond returns. Equity characteristics may generate incremental prediction power for two reasons (Bali et al., 2022). First, both stocks and bonds represent claims on the same underlying assets of the firm; Second, bonds and stocks should be jointly priced based on the structural credit risk model of Merton (1974). To investigate the incremental role of characteristics, we add 21 more stock characteristics into our models by following He et al. (2021) and Gu et al. (2020).

[Insert Table 8 Here]

The third row of Panel A of Table 8 presents that the predicting performance of most of our models improves after including stock characteristics, with $\bar{R}^2_{OOS,t}$ difference varying from -0.08% for LASSO to -0.38% for NN3. However, only RIDGE, ENet and PLS models generate significant $\bar{R}^2_{OOS,t}$ difference, with $\bar{R}^2_{OOS,t}$ difference of -0.25% (*t-stat*= -4.86), -0.21% (*t-stat*= -2.03) and -0.22% (*t-stat*= -2.03), respectively. Moreover, we find a significant deteriorated predicting performance for GBRT and NN1 models, with $\bar{R}^2_{OOS,t}$ difference of 0.24% (*t-stat*= 2.77) and 0.60% (*t-stat*= 1.76) respectively. In general, we fail to find consistent results of significant predicting improvement by including stock predictors across all models. This is consistent with the findings of He et al. (2021) and Bali et al. (2022).

We also find similar mixed results for non-U.S. developed and emerging markets as presented in panel B and panel C of Table 8. Particularly, stock characteristics' incremental predictive power relative to bond characterises and macro variables are only significant for two of eleven models (including OLS) in non-U.S. developed market (LASSO and ENet) and three in emerging market (RIDGE, PLS and NN1).

4. Conclusion

Growing number of studies have devoted to the cross-section of corporate bond returns in the U.S. market. However, limited data availability prevents research in international corporate bond market. With a novel international dataset, this paper is, to our knowledge, the first to introduce machine learning techniques to make a thorough analysis of the out-of-sample predictability of international corporate bond returns. We first divide international corporate bond market into three markets: U.S., non-U.S. developed and emerging. We find that machine learning models outperform traditional OLS in terms of out-of-sample predictability and long-short portfolio strategy profits in all of these three markets.

We also find that return predictors of corporate bonds in non-U.S. markets, especially in emerging market, are substantially different from U.S. market. Macroeconomic variables (especially inflation), downside risk, interest-rate risk, illiquidity, and volatility are more important to improve corporate return predictability in emerging market than in U.S. market, while short-term reversal, co-skewness, exposure to size risk, and exposure to market risk are the most important predictors in U.S. Moreover, additional equity and bond factors (MKT, SMB, HML, DEF and excess bond market return) from U.S. market fail to enhance the predicting performance, indicating that international corporate bond markets are not well integrated.

References

Ahir, H., Bloom, N., and Furceri, D. (2022). The world uncertainty index. NBER working paper No. w29763.

Amihud, Y., and Mendelson, H. (1986). Liquidity and stock returns. *Financial Analysts Journal*, 42(3), 43-48.

Avramov, D., Chordia, T., and Goyal, A. (2006). Liquidity and autocorrelations in individual stock returns. *The Journal of Finance*, 61(5), 2365-2394.

Bai, J., Bali, T. G., and Wen, Q. (2019). Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics*, 131(3), 619-642.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593-1636.

Bali, T. G., Goyal, A., Huang, D., Jiang, F., and Wen, Q. (2022). Different strokes: Return predictability across stocks and bonds with machine learning and big data. Working paper.

Bali, T. G., Subrahmanyam, A., and Wen, Q. (2021). Long-term reversals in the corporate bond market. *Journal of Financial Economics*, 139(2), 656-677.

Bao, J., Chen, J., Hou, K., and Lu, L. (2021). Prices and volatilities in the corporate bond market. Working Paper.

Bartram, S. M., Grinblatt, M., and Nozawa, Y. (2020). Book-to-market, mispricing, and the cross-section of corporate bond returns. (). NBER working paper No. w27655.

Bekaert, G., and De Santis, R. A. (2021). Risk and return in international corporate bond markets. *Journal of International Financial Markets, Institutions and Money*, 72, 101338.

Bekaert, G., Hodrick, R. J., and Zhang, X. (2009). International stock return comovements. *The Journal of Finance*, 64(6), 2591-2626.

Bianchi, D., Büchner, M., and Tamoni, A. (2021). Bond risk premiums with machine learning. *The Review of Financial Studies*, 34(2), 1046-1089.

Bongaerts, D., De Jong, F., and Driessen, J. (2017). An asset pricing approach to liquidity effects in corporate bond markets. *The Review of Financial Studies*, 30(4), 1229-1269.

Boyer, B., Mitton, T., and Vorkink, K. (2010). Expected idiosyncratic skewness. *The Review of Financial Studies*, 23(1), 169-202.

Caldara, D., and Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, 112(4), 1194-1225.

Chaieb, I., Langlois, H., and Scaillet, O. (2021). Factors and risk premia in individual international stock returns. *Journal of Financial Economics*, 141(2), 669-692.

Choi, D., Jiang, W., and Zhang, C. (2022). Alpha go everywhere: Machine learning and international stock returns. Working paper.

Chung, K. H., Wang, J., and Wu, C. (2019). Volatility and the cross-section of corporate bond returns. *Journal of Financial Economics*, 133(2), 397-417.

Crawford, S. S., Perotti, P., Price III, R. A., and Skousen, C. J. (2019). Financial statement anomalies in the bond market. *Financial Analysts Journal*, 75(3), 105-124.

Dong, X., Li, Y., Rapach, D. E., and Zhou, G. (2022). Anomalies and the expected market return. *The Journal of Finance*, 77(1), 639-681.

Elkamhi, R., Jo, C., and Nozawa, Y. (2021). A one-factor model of corporate bond premia. Working paper.

Fama, E. F., and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56.

Feng, G., Giglio, S., and Xiu, D. (2020). Taming the factor zoo: A test of new factors. *The Journal of Finance*, 75(3), 1327-1370.

Freyberger, J., Neuhierl, A., and Weber, M. (2020). Dissecting characteristics nonparametrically. *The Review of Financial Studies*, 33(5), 2326-2377.

Gebhardt, W. R., Hvidkjaer, S., and Swaminathan, B. (2005). The cross-section of expected corporate bond returns: Betas or characteristics?. *Journal of Financial Economics*, 75(1), 85-114.

Giglio, S., Liao, Y., and Xiu, D. (2021). Thousands of alpha tests. *The Review of Financial Studies*, 34(7), 3456-3496.

Goyal, A., and Welch, I. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, 21(4), 1455-1508.

Griffin, J. M. (2002). Are the Fama and French factors global or country specific?. *The Review of Financial Studies*, 15(3), 783-803.

Gu, S., Kelly, B., and Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5), 2223-2273.

He, A., Huang, D., Li, J., and Zhou, G. (2022). Shrinking Factor Dimension: A Reduced-Rank Approach. Working paper.

He, X., Feng, G., Wang, J., and Wu, C. (2021). Predicting Individual Corporate Bond Returns. Working paper.

Hollstein, F. (2022). Local, Regional, or Global Asset Pricing?. *Journal of Financial and Quantitative Analysis*, 57(1), 291-320.

Hou, K., Karolyi, G. A., and Kho, B. C. (2011). What factors drive global stock returns?. *The Review of Financial Studies*, 24(8), 2527-2574.

Hou, K., Xue, C., and Zhang, L. (2020). Replicating anomalies. *The Review of Financial Studies*, 33(5), 2019-2133.

Huang, J. Z., and Shi, Z. (2021). What do we know about corporate bond returns?. *Annual Review of Financial Economics*, 13(1), 363-399.

Jostova, G., Nikolova, S., Philipov, A., and Stahel, C. W. (2013). Momentum in corporate bond returns. *The Review of Financial Studies*, 26(7), 1649-1693.

Kozak, S., Nagel, S., and Santosh, S. (2020). Shrinking the cross-section. *Journal of Financial Economics*, 135(2), 271-292.

Lee, M., Rizova, S., and Wang, S. (2022). The cross-section of global corporate bond returns. Working paper.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, 105(1), 1-28.

Leippold, M., Wang, Q., and Zhou, W. (2021). Machine learning in the Chinese stock market. *Journal of Financial Economics*.

Li, D., Magud, M. N. E., Werner, A. M., & Witte, S. (2021). The long-run impact of sovereign yields on corporate yields in emerging markets. IMF Working paper.

Lin, H., Wang, J., and Wu, C. (2011). Liquidity risk and expected corporate bond returns. *Journal of Financial Economics*, 99(3), 628-650.

Lin, H., Wu, C., and Zhou, G. (2018). Forecasting corporate bond returns with a large set of predictors: An iterated combination approach. *Management Science*, 64(9), 4218-4238.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2), 449-470.

Schestag, R., Schuster, P., and Uhrig-Homburg, M. (2016). Measuring liquidity in bond markets. *The Review of Financial Studies*, 29(5), 1170-1219.

Valenzuela, P. (2016). Rollover risk and credit spreads: Evidence from international corporate bonds. *The Review of Finance*, 20(2), 631-661.

Appendix: Characteristics Descriptions

A. Corporate Bond Characteristics (20)

1. **Credit Rating (*Rating*).** We obtain bond-level rating information from Bloomberg. Credit ratings are turned to conventional linear numeric scores where higher numerical score means higher credit risk (AAA = 1, AA+ = 2, …, C = 21). When two or more ratings are provided by Standard & Poor's, Moody's, and Fitch, the ratings are averaged.
2. **Time-to-maturity (*MAT*).** The number of years to maturity.
3. **Age (*Age*). The n**umber of years since bonds' issuance.
4. **Duration (*DUR*).** The Macaulay duration, obtained from IHS Markit data.
5. **Issuance size (Size).** The natural logarithm of bond amount issued, obtained from Bloomberg.
6. **Illiquidity (*ILLIQ_Bond*).** Following Amihud and Mendelson (1986), we first calculate relative bid-ask spread as ask price minus bid price, divided by average of bid and ask prices for each day. Then, we take the mean of daily values in a week to get a weekly illiquidity proxy for each bond.
7. **Volatility (*VOL*).** We estimate historical volatility using daily return for past month.
8. **Skewness (*SKEW*).** We estimate historical skewness using daily return for past month.
9. **Kurtosis (*KURT*).** We estimate historical Kurtosis using daily return for past month.
10. **Downside risk (*VaR5*)**. Following Bai et al. (2019), we measure downside risk of corporate bonds using the second lowest daily return observation over the past 36 trading days. For convenience of interpretation, we multiply the original measure by −1.
11. **Short-term reversal (*REV_Bond*).** Following Lehmann (1990) and Avramov, Chordia, and Goyal (2006), we measure short-term reversal using bond return in previous week.
12. **Four-week momentum (*MOM4Bond*).** Lagged 2-week to lagged 4-week cumulative weekly returns.
13. **Twelve-week momentum (*MOM12Bond*).** Lagged 2-week to lagged 12-week cumulative weekly returns.
14. **Bond market beta (*BETA_BMKT*).** Following Bali et al. (2022), we estimate bond market beta of individual bonds on bond market excess return using the rolling sample of the past 26 weeks. Bond market excess return is computed as the value-weighted (amount issuance as weight) average returns of all corporate bonds for each of the three markets minus the risk-free rate.
15. **Market beta (*BETA_MKT*).** Following Fama and French (1993), we estimate market beta of individual bonds on market factor obtained from French's website using the rolling sample of the past 26 weeks.
16. **Size beta (*BETA_SMB*).** Following Fama and French (1993), we estimate market beta of individual bonds on size factor obtained from French's website using the rolling sample of the past 26 weeks.
17. **Value beta (*BETA_HML*).** Following Fama and French (1993), we estimate market beta of individual bonds on value factor obtained from French's website using the rolling sample of the past 26 weeks.

18. **Term beta (*BETA_TERM*).** Following Fama and French (1993) and Crawford, Perotti, Price III and Skousen (2019), we estimate term beta of individual bonds on *TERM* factor using the rolling sample of the past 26 weeks. *TERM* factor is defined as $TERM = r_{SBTSY10} – r_f$, where $r_{SBTSY10}$ is the return on long-term government bonds based on *SBTSY10* index (a 10-year constant-maturity price index) from Bloomberg.
19. **Default beta** (***BETA_DEF***). Following Fama and French (1993) and Crawford et al. (2019), we estimate default beta of individual bonds on *DEF* factor using the rolling sample of the past 26 weeks. *DEF* factor is calculated as $DEF = r_{Sample} - r_{SBTSY10}$, where r_{Sample} is the return on investment-grade corporate bonds with more than 10 years to maturity for each of the three markets, weighted by amount issued.
20. **Co-skewness (*COSKEW*).** Following Boyer, Mitton, and Vorkink (2010), co-skewness is estimated based on the following rolling regressions of the past 26 weeks:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_i R_{m,t}^2 + \varepsilon_{i,t,}$$

where $R_{i,t}$ is weekly excess return of bond i, $R_{m,t}$ is weekly bond market excess return for each of the three markets, and γ_i is co-skewness (systematic skewness) of bond i.

B. Macro variables (6)

1. **U.S. exchange rate growth (*USExGrowth*).** The nominal U.S. dollar exchange rate weekly growth, obtained from Datastream.
2. **GDP growth (*GDPGrowth*).** Quarter-over-quarter real GDP quarterly growth, obtained from IMF internal databases.
3. **inflation** (*CPIGrowth*). Monthly inflation, obtained from IMF internal databases.
4. **Geopolitical risk (*GPRChange*).** The log change of monthly geopolitical risk index from Caldara and Iacoviello (2022).
5. **Economic policy uncertainty (*EPUChange*).** The log change of monthly economic policy uncertainty index from Baker, Bloom, and Davis (2016).
6. **World uncertainty (*WUIChange*).** The log change of world uncertainty index from Ahir, Bloom and Furceri (2022).

C. Stock Characteristics (21)

Following He et al. (2021), we first construct 15 out of 20 stock characteristics based on the variable definitions from Hou, Xue and Zhang (2020).[8] We also select several most important stock characteristics from Figure 5 of Gu et al. (2020).

[8] We obtain stock pricing and accounting information from Datastream rather than Compustat in He et al. (2021) and Hou et al. (2020), and our analysis is for weekly bond returns. We change the constructions slightly for some stock characteristics if needed.

C.1 Stock Characteristics from He et al. (2021)

1. **Standard Unexpected Earnings (*SUE*).** The change of split-adjusted quarterly earnings per share from its value one year ago scaled by standard deviation of this change over the prior two years.
2. **Cumulative abnormal returns around earnings announcement dates (*ABR*).** The cumulative abnormal stock daily return around the latest quarterly earnings announcement date.
3. **Revisions in analyst earnings forecasts (*RE*).** The 6-month moving average of past changes in analysts' forecasts.
4. **Twelve-week momentum (*MOM12Stock*).** Lagged 2-week to lagged 12-week cumulative weekly returns.
5. **Book-to-Market (*BM*).** Yearly book equity to weekly market equity.
6. **Earnings to price (*EP*).** Quarterly earnings to weekly price.
7. **Cashflow to price (*CFP*).** Quarterly cashflow to weekly price.
8. **Sales to price (*SP*).** Quarterly sales to weekly price.
9. **Asset Growth Rate (*AGR*).** Quarterly asset Growth Rate.
10. **Quarterly equity issuance (*NI*).** Quarterly equity issuance.
11. **Return on asset (*ROA*).** Quarterly return on quarterly asset.
12. **Market equity (*ME*).** Weekly market equity.
13. **Stock variance (*SVAR*).** We estimate historical volatility using daily return for the past month.
14. **CAPM beta (*BETA*).** Following Fama and French (1993), we estimate market beta of individual stocks on value-weighted average market excess returns using the rolling sample of the past 26 weeks.
15. **Short-term reversal (*REV_Stock*).** Following Lehmann (1990) and Avramov et al. (2006), we measure short-term reversal using the stock return in previous week.

C.2 Stock Characteristics from Gu et al. (2020)

1. **Cumulative weekly returns on prior 2-4 weeks (*MOM4Stock*)**
2. **Idiosyncratic risk (*IDIOVOL*).** Standard deviation of residuals of weekly returns on weekly value-weighted market excess returns for past 26 weeks.
3. **Maximum daily return (*MAXRET*).** Maximum daily return in a week.
4. **Amihud illiquidity (*ILLIQ_Stock*).** Weekly average of daily absolute return divided by dollar volume.
5. **Bid-ask spread (*BASPREAD*).** Weekly average of daily bid-ask spread divided by average of daily bid and ask price.
6. **Share turnover (*TURN*).** Average weekly trading volume for most recent 3 weeks scaled by shares outstanding.

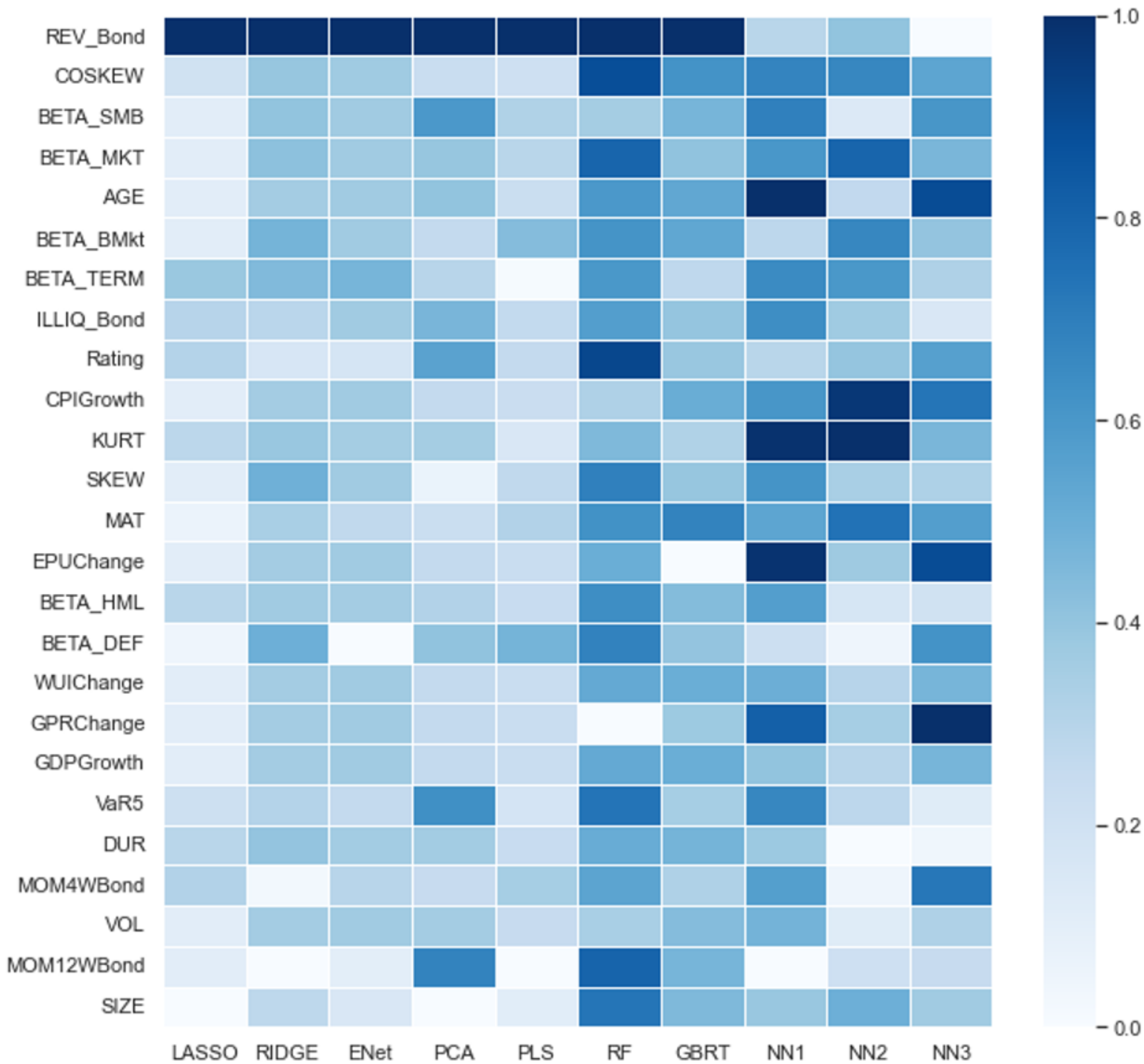

Figure 1: Characteristic Importance in the U.S. Market

This figure presents the overall rankings of 20 bond characteristics and 5 macro variables (excluding *USExGrowth*) based on variable importance in each model in the U.S. market. To measure variable importance, we first calculate the reduction of time-series average weekly R-squared $\bar{R}^2_{OOS,t}$ from setting all values of a given predictor to zero, while keeping the remaining predictors unchanged. Variable importance is defined as the relative reduction of $\bar{R}^2_{OOS,t}$. In this way, the characteristic with lowest R-squared reduction has variable importance of 0, while the characteristic with highest R-squared reduction has variable importance of 1. To get the overall rankings of characteristics across models, we rank the importance of each characteristic for each model and then average them into a single rank. Columns correspond to individual models, and color gradients within each column indicate the most influential (dark blue) to least influential (white) characteristics.

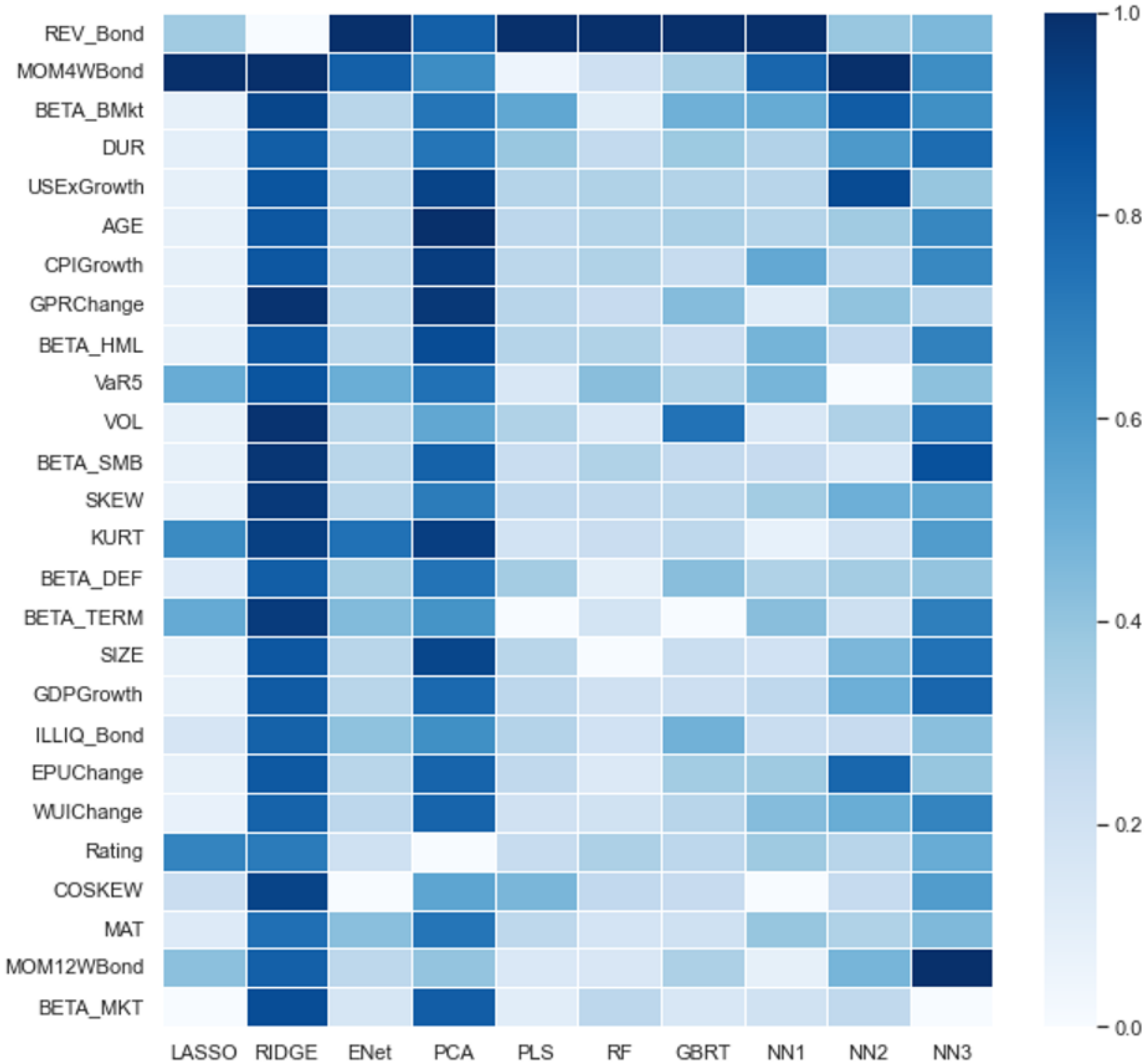

Figure 2: Characteristic Importance in the Non-U.S. Developed Market

This figure presents the overall rankings of 20 bond characteristics and 5 macro variables (excluding *USExGrowth*) based on variable importance in each model in the non-U.S. developed market. To measure variable importance, we first calculate the reduction of time-series average weekly *R*-squared $\bar{R}^2_{OOS,t}$ from setting all values of a given predictor to zero, while keeping the remaining predictors unchanged. Variable importance is defined as the relative reduction of $\bar{R}^2_{OOS,t}$. In this way, the characteristic with lowest *R*-squared reduction has variable importance of 0, while the characteristic with highest *R*-squared reduction has variable importance of 1. To get the overall rankings of characteristics across models, we rank the importance of each characteristic for each model and then average them into a single rank. Columns correspond to individual models, and color gradients within each column indicate the most influential (dark blue) to least influential (white) characteristics.

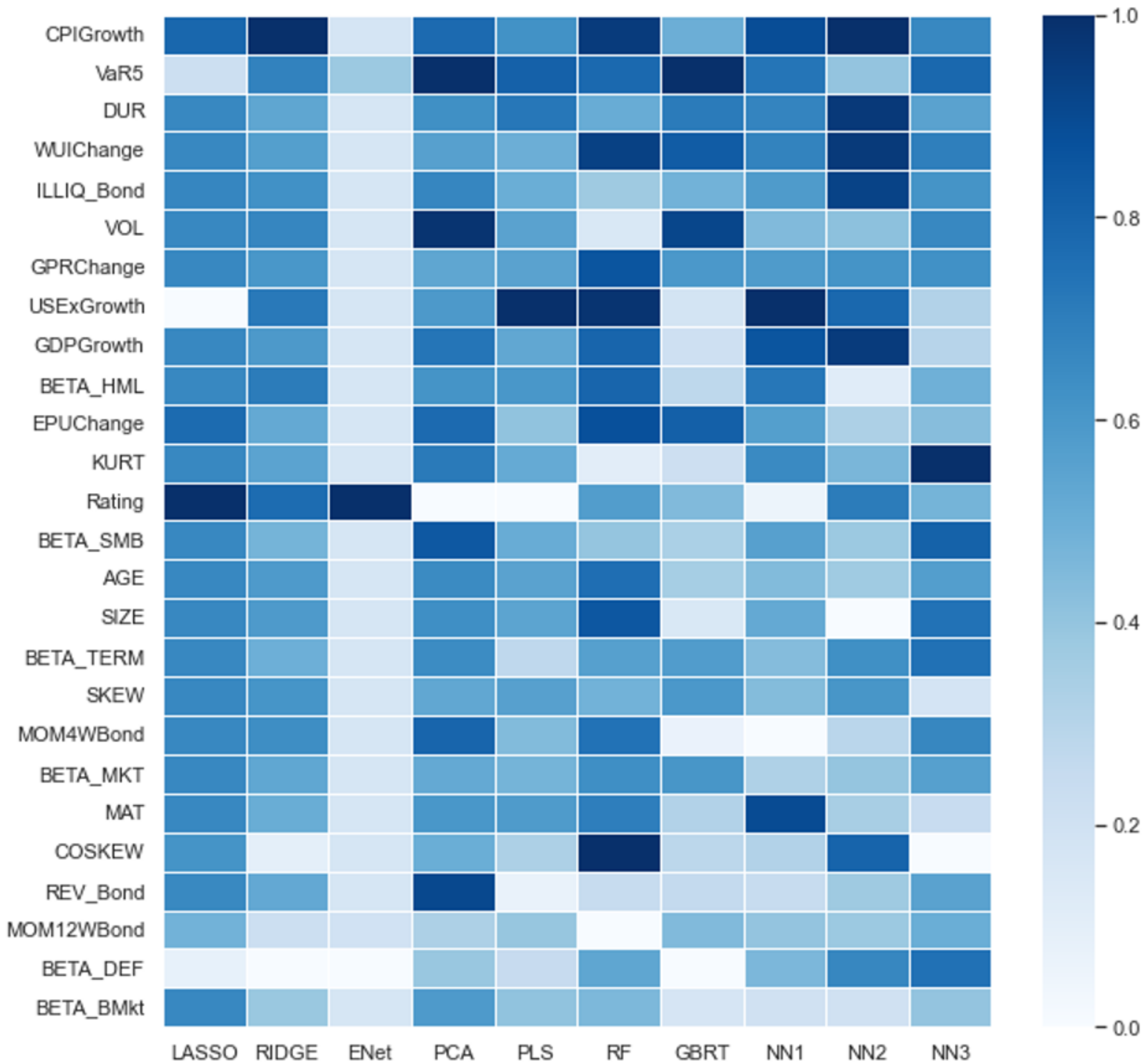

Figure 3: Characteristic Importance in the Emerging Market

This figure presents the overall rankings of 20 bond characteristics and 5 macro variables (excluding *USExGrowth*) based on variable importance in each model in the emerging market. To measure variable importance, we first calculate the reduction of time-series average weekly *R*-squared $\bar{R}^2_{OOS,t}$ from setting all values of a given predictor to zero, while keeping the remaining predictors unchanged. Variable importance is defined as the relative reduction of $\bar{R}^2_{OOS,t}$. In this way, the characteristic with lowest *R*-squared reduction has variable importance of 0, while the characteristic with highest *R*-squared reduction has variable importance of 1. To get the overall rankings of characteristics across models, we rank the importance of each characteristic for each model and then average them into a single rank. Columns correspond to individual models, and color gradients within each column indicate the most influential (dark blue) to least influential (white) characteristics.

Table 1: Sample Distribution

This table reports sample distribution for three markets, i.e., U.S. market, non-U.S. developed market, and emerging market. To identify the nationality of each bond, we obtain the country of risk from Bloomberg based on bond's International Securities Identification Numbers (ISIN's). *Number of obs.* indicates the number of weekly observations for each market. *Number of bonds* indicates the number of unique bond ISINs corresponding to each market. *Number of companies* indicates the number of unique equity ISINs corresponding to each market. Proportions of each of these three markets to the whole sample are reported in the parentheses.

	Number of obs.	Number of bonds	Number of companies
US	998,775 (77%)	9,869 (75%)	1,129 (56%)
Non-U.S. developed	167,119 (13%)	1,849 (14%)	320 (16%)
Emerging	131,112 (10%)	1,501 (11%)	550 (28%)
Total	1,297,006	13,219	1,999

Table 2: Descriptive Statistics

This table reports the number of bond-week observations, cross-sectional mean, median, standard deviation and percentiles of weekly corporate bond returns, credit rating, time to maturity, age, duration, size, illiquidity and downside risk in U.S. market (Panel A), non-U.S. developed market (Panel B) and emerging market (Panel C). Credit ratings are reported in conventional linear numeric scores where higher numerical score means higher credit risk (AAA = 1, AA+ = 2, …, C = 21). Size is the natural logarithm of amount issued. Following Amihud and Mendelson (1986), illiquidity is measured by relative bid-ask spread to actual spread, divided by average of bid and ask prices. Downside risk is proxied by 5% Value-at-Risk (VaR), i.e., the second lowest daily return over the past 36 trading days.

	N	Mean	Media	SD	1st	p5	p25	p75	p95	99th
Panel A: U.S.										
Bond return (%, weekly)	998,775	0.06	0.04	0.56	-1.34	-0.81	-0.26	0.35	1.02	1.52
Rating (AAA = 1, AA+ = 2, etc.)	998,775	8.42	8.00	3.01	1.61	4.16	6.46	9.94	14.39	16.99
Time to maturity (years)	998,775	9.87	6.40	9.68	0.64	1.13	3.41	13.83	27.27	35.58
Age (years)	998,775	6.69	4.59	6.08	0.83	1.16	2.64	8.07	20.57	25.91
Duration	704,733	6.44	5.24	4.81	0.58	1.01	3.03	9.11	15.16	16.92
Size	998,190	5.52	6.05	1.82	0.48	1.33	5.35	6.61	7.60	8.05
Illiquidity	992,082	0.55	0.43	0.56	0.03	0.07	0.23	0.77	1.32	1.92
Downside risk (5% VaR)	992,082	0.58	0.45	0.56	0.00	0.05	0.23	0.81	1.43	2.49
Panel B: Non-U.S. developed										
Bond return (%, weekly)	167,119	0.05	0.03	0.48	-1.20	-0.68	-0.19	0.26	0.87	1.41
Rating (AAA = 1, AA+ = 2, etc.)	167,119	7.30	7.24	3.07	1.00	3.44	5.13	9.00	13.75	16.07
Time to maturity (years)	167,119	7.71	4.66	8.36	0.59	0.90	2.41	8.64	25.58	28.81
Age (years)	167,119	5.25	3.73	4.82	0.81	1.00	2.07	6.48	16.58	22.52
Duration	145,959	5.26	3.95	4.09	0.56	0.84	2.17	7.00	14.27	16.07
Size	167,119	6.38	6.60	1.18	1.02	4.22	6.12	7.04	7.61	7.98
Illiquidity	166,236	0.44	0.32	0.42	0.03	0.06	0.16	0.61	1.19	1.67
Downside risk (5% VaR)	166,236	0.48	0.34	0.57	0.01	0.06	0.17	0.63	1.31	2.11
Panel C: Emerging										
Bond return (%, weekly)	131,112	0.07	0.06	0.49	-1.24	-0.73	-0.14	0.28	0.94	1.49
Rating (AAA = 1, AA+ = 2, etc.)	131,112	9.86	9.97	3.33	3.68	4.63	7.39	12.05	15.56	17.65
Time to maturity (years)	131,112	5.85	3.81	7.23	0.60	0.91	2.19	6.44	23.20	28.12
Age (years)	131,112	4.19	3.51	3.50	0.82	1.03	1.97	5.03	9.95	20.79
Duration	126,827	4.18	3.37	3.29	0.47	0.78	1.94	5.35	12.31	15.21
Size	131,112	6.27	6.22	0.59	4.62	5.30	5.92	6.62	7.27	7.60
Illiquidity	130,402	0.63	0.52	0.76	0.06	0.11	0.32	0.75	1.40	2.92
Downside risk (5% VaR)	130,402	0.45	0.29	0.59	0.00	0.05	0.14	0.55	1.32	2.62

Table 3: Prediction Performance of Machine Learning Models

This table reports out of sample prediction performance (R^2_{OOS}) of machine leaning models in U.S. market (Panel A), non-U.S. developed market (Panel B) and emerging market (Panel C). We use 20 bond characteristics and 6 macro variables for non-U.S. developed market and emerging market, and 25 characteristics (excluding *USExGrowth*) for U.S. market. For each market, bonds are sorted into investment grade bonds (with ratings of 10 or below, i.e., BBB- or better) and non-investment grade (with ratings of 11 or higher, i.e., BB+ or worse). Machine learning models include OLS, LASSO, ridge regression (RIDGE), elastic net (ENet), principal component analysis (PCA), partial least square (PLS), random forest (RF), gradient boosted regression trees (GBRT) and neural networks with one to five layers (NN1–NN3).

	OLS	LASSO	RIDGE	ENet	PCA	PLS	RF	GBRT	NN1	NN2	NN3
Panel A: U.S.											
All bonds	-2.67	3.26	2.97	3.04	2.89	3.09	3.21	3.03	1.94	3.03	3.27
Investment-grade	-3.47	4.20	4.05	4.04	4.00	4.28	4.75	3.73	1.82	5.37	4.86
Non-investment-grade	-2.30	-0.83	-0.61	-0.83	-0.57	-0.77	-0.80	-0.64	-0.31	-0.18	0.23
Panel B: Non-U.S. developed											
All bonds	-3.52	2.83	2.05	2.91	2.92	2.94	3.29	2.85	2.93	2.85	2.82
Investment-grade	-4.30	4.37	3.15	4.56	5.00	4.94	4.59	3.35	4.80	3.96	4.22
Non-investment-grade	-3.40	-1.81	-1.89	-1.84	-2.45	-3.19	-1.98	-1.85	-3.02	-1.50	-1.62
Panel C: Emerging											
All bonds	-2.14	3.06	3.12	3.19	3.41	2.93	3.28	3.32	2.81	3.39	3.72
Investment-grade	-4.21	4.45	4.45	4.42	5.10	3.97	5.34	4.53	3.87	4.80	4.47
Non-investment-grade	0.15	2.43	2.46	2.33	2.50	2.54	2.21	2.24	2.75	2.70	2.78

Table 4: Value-weighted Performance of Machine Learning Portfolios

This table reports out of sample performance of prediction-sorted portfolios in U.S. (Panel A), non-U.S. developed market (Panel B) and emerging market (Panel C). We use 20 bond characteristics and 6 macro variables for non-U.S. developed market and emerging market, and 25 characteristics (excluding *USExGrowth*) for U.S. market. At the end of each week, we sort bonds into deciles based on each model's one-week-ahead out-of-sample bond return predictions and construct value-weighted portfolio, using amount issued as weights. We report annualized Sharpe ratio of long-short portfolio and time-series average weekly returns for each decile and long-short portfolio. Newey-West t-stats for long-short portfolio returns are reported in the parentheses.

	Low	2	3	4	5	6	7	8	9	High	High-Low	High-Low SR
Panel A: U.S.												
OLS	0.02	0.08	0.10	0.10	0.09	0.09	0.10	0.11	0.13	0.16	0.14 (1.82)	1.03
LASSO	-0.02	0.06	0.08	0.10	0.08	0.08	0.09	0.12	0.15	0.20	0.22 (6.69)	1.86
RIDGE	-0.03	0.03	0.06	0.07	0.09	0.10	0.12	0.14	0.17	0.20	0.22 (3.89)	1.82
ENet	-0.01	0.07	0.09	0.09	0.09	0.08	0.08	0.11	0.14	0.19	0.21 (6.47)	1.73
PCA	-0.01	0.05	0.07	0.07	0.09	0.10	0.11	0.14	0.17	0.19	0.18 (6.42)	1.71
PLS	-0.01	0.05	0.06	0.07	0.10	0.10	0.13	0.14	0.17	0.19	0.20 (5.44)	1.88
RF	0.00	0.02	0.05	0.10	0.10	0.08	0.08	0.11	0.15	0.23	0.22 (2.73)	1.62
GBRT	0.04	0.04	0.08	0.09	0.07	0.08	0.08	0.10	0.15	0.24	0.19 (2.46)	1.40
NN1	0.02	0.05	0.06	0.08	0.09	0.10	0.09	0.11	0.18	0.20	0.17 (4.88)	1.42
NN2	0.01	0.04	0.05	0.07	0.08	0.10	0.10	0.13	0.18	0.21	0.19 (4.53)	1.63
NN3	0.02	0.07	0.07	0.07	0.08	0.08	0.08	0.13	0.16	0.22	0.20 (5.60)	1.61
Panel B: Non-U.S. developed												
OLS	0.05	0.06	0.08	0.08	0.08	0.08	0.08	0.06	0.10	0.15	0.11 (1.16)	0.87
LASSO	0.04	0.05	0.06	0.06	0.08	0.08	0.09	0.10	0.15	0.17	0.15 (2.20)	1.19
RIDGE	0.00	0.02	0.04	0.07	0.09	0.10	0.11	0.11	0.16	0.17	0.17 (1.64)	1.27
ENet	0.04	0.04	0.06	0.06	0.08	0.07	0.08	0.11	0.14	0.17	0.14 (2.00)	1.11
PCA	0.03	0.05	0.05	0.07	0.07	0.07	0.08	0.11	0.15	0.16	0.13 (1.62)	1.07
PLS	0.02	0.04	0.06	0.06	0.07	0.09	0.09	0.10	0.17	0.18	0.16 (2.00)	1.40
RF	0.05	0.04	0.05	0.07	0.09	0.09	0.08	0.06	0.08	0.22	0.18 (1.61)	1.32
GBRT	0.05	0.05	0.05	0.07	0.10	0.10	0.07	0.08	0.08	0.19	0.13 (1.18)	1.00
NN1	0.03	0.04	0.04	0.06	0.07	0.10	0.10	0.08	0.15	0.19	0.16 (2.22)	1.50
NN2	0.02	0.04	0.05	0.06	0.08	0.10	0.09	0.10	0.12	0.20	0.16 (2.21)	1.48
NN3	0.01	0.04	0.05	0.07	0.07	0.08	0.10	0.09	0.12	0.21	0.19 (2.64)	1.92

Panel C: Emerging

OLS	0.18	0.13	0.10	0.11	0.07	0.06	0.08	0.06	0.11	0.15	-0.04 (-0.60)	-0.33
LASSO	0.05	0.06	0.07	0.08	0.08	0.10	0.12	0.14	0.15	0.18	0.14 (2.26)	1.06
RIDGE	0.04	0.06	0.08	0.08	0.08	0.11	0.13	0.11	0.12	0.22	0.18 (2.57)	1.45
ENet	0.05	0.06	0.07	0.09	0.07	0.11	0.11	0.14	0.15	0.18	0.14 (1.92)	1.05
PCA	0.04	0.06	0.08	0.07	0.09	0.12	0.13	0.12	0.13	0.21	0.17 (2.74)	1.44
PLS	0.05	0.07	0.08	0.09	0.09	0.10	0.12	0.12	0.10	0.21	0.15 (2.14)	1.23
RF	0.05	0.08	0.07	0.07	0.10	0.10	0.11	0.14	0.14	0.22	0.18 (2.69)	1.31
GBRT	0.07	0.08	0.09	0.05	0.07	0.09	0.12	0.11	0.17	0.21	0.16 (2.53)	1.17
NN1	0.08	0.08	0.07	0.08	0.07	0.08	0.08	0.11	0.15	0.23	0.15 (2.92)	1.33
NN2	0.07	0.06	0.07	0.09	0.10	0.09	0.10	0.10	0.13	0.24	0.19 (3.61)	1.65
NN3	0.05	0.07	0.08	0.08	0.10	0.08	0.11	0.10	0.12	0.25	0.19 (3.31)	1.71

Table 5: Equal-weighted Performance of Machine Learning Portfolios

This table reports out of sample performance of prediction-sorted portfolios in U.S. (Panel A), non-U.S. developed market (Panel B) and emerging market (Panel C). We use 20 bond characteristics and 6 macro variables for non-U.S. developed market and emerging market, and 25 characteristics (excluding *USExGrowth*) for U.S. market. At the end of each week, we sort bonds into deciles based on each model's one-week-ahead out-of-sample bond return predictions and construct equal-weighted portfolio. We report annualized Sharpe ratio of long-short portfolio and time-series average weekly returns for each decile and long-short portfolio. Newey-West t-stats for long-short portfolio returns are reported in the parentheses.

	Low	2	3	4	5	6	7	8	9	High	High-Low	High-Low SR
Panel A: U.S.												
OLS	0.01	0.06	0.09	0.09	0.09	0.09	0.10	0.11	0.13	0.16	0.15 (2.05)	1.15
LASSO	-0.01	0.05	0.08	0.09	0.08	0.08	0.09	0.12	0.16	0.20	0.21 (7.49)	1.71
RIDGE	-0.02	0.03	0.05	0.06	0.08	0.10	0.12	0.14	0.17	0.19	0.22 (4.47)	1.70
ENet	-0.01	0.06	0.09	0.08	0.08	0.08	0.09	0.11	0.15	0.19	0.20 (7.24)	1.60
PCA	0.00	0.04	0.06	0.06	0.08	0.10	0.12	0.13	0.16	0.18	0.17 (5.87)	1.49
PLS	-0.01	0.04	0.05	0.07	0.08	0.10	0.12	0.13	0.16	0.19	0.20 (6.15)	1.72
RF	0.01	0.02	0.05	0.10	0.10	0.06	0.08	0.13	0.16	0.22	0.21 (2.99)	1.55
GBRT	0.03	0.04	0.07	0.08	0.07	0.07	0.09	0.12	0.13	0.23	0.20 (2.60)	1.42
NN1	0.03	0.06	0.05	0.06	0.08	0.09	0.09	0.11	0.16	0.19	0.16 (5.44)	1.26
NN2	0.02	0.04	0.04	0.06	0.08	0.09	0.11	0.13	0.16	0.19	0.18 (5.80)	1.38
NN3	0.02	0.05	0.06	0.07	0.08	0.09	0.09	0.11	0.15	0.22	0.20 (5.84)	1.50
Panel B: Non-U.S. developed												
OLS	0.02	0.07	0.07	0.08	0.08	0.08	0.08	0.07	0.11	0.15	0.13 (1.64)	1.08
LASSO	0.02	0.04	0.05	0.06	0.06	0.07	0.09	0.11	0.14	0.18	0.17 (2.65)	1.40
RIDGE	-0.01	0.02	0.04	0.06	0.08	0.09	0.12	0.12	0.14	0.17	0.18 (1.82)	1.32
ENet	0.02	0.04	0.05	0.07	0.07	0.07	0.08	0.12	0.14	0.18	0.16 (2.43)	1.32
PCA	0.01	0.05	0.05	0.07	0.07	0.08	0.09	0.11	0.14	0.16	0.15 (1.97)	1.23
PLS	0.00	0.03	0.05	0.06	0.06	0.09	0.11	0.10	0.15	0.18	0.17 (2.21)	1.46
RF	0.05	0.05	0.05	0.07	0.10	0.09	0.09	0.06	0.06	0.23	0.18 (1.61)	1.30
GBRT	0.06	0.05	0.04	0.06	0.10	0.10	0.07	0.08	0.08	0.19	0.13 (1.14)	0.96
NN1	0.03	0.04	0.04	0.06	0.07	0.09	0.09	0.09	0.13	0.19	0.16 (2.27)	1.46
NN2	0.02	0.04	0.05	0.05	0.08	0.09	0.09	0.10	0.13	0.18	0.16 (2.26)	1.46
NN3	0.02	0.04	0.05	0.06	0.07	0.07	0.09	0.10	0.13	0.20	0.18 (2.54)	1.80

Panel C: Emerging

OLS	0.20	0.14	0.11	0.10	0.07	0.06	0.07	0.07	0.11	0.14	-0.06 (-0.91)	-0.48
LASSO	0.05	0.06	0.07	0.09	0.08	0.11	0.12	0.14	0.16	0.19	0.13 (2.15)	1.02
RIDGE	0.04	0.06	0.08	0.09	0.08	0.12	0.14	0.12	0.12	0.22	0.18 (2.56)	1.45
ENet	0.05	0.06	0.07	0.09	0.08	0.11	0.12	0.15	0.15	0.19	0.14 (1.83)	1.01
PCA	0.04	0.06	0.08	0.08	0.10	0.13	0.12	0.11	0.14	0.22	0.18 (2.75)	1.45
PLS	0.05	0.07	0.08	0.09	0.10	0.11	0.12	0.13	0.12	0.20	0.15 (2.2)	1.24
RF	0.05	0.07	0.08	0.07	0.11	0.09	0.10	0.13	0.14	0.23	0.18 (2.69)	1.31
GBRT	0.07	0.07	0.09	0.06	0.08	0.08	0.12	0.12	0.16	0.22	0.15 (2.47)	1.14
NN1	0.09	0.08	0.07	0.08	0.08	0.08	0.10	0.12	0.14	0.23	0.14 (2.79)	1.22
NN2	0.08	0.06	0.07	0.09	0.10	0.10	0.10	0.11	0.13	0.25	0.18 (3.37)	1.53
NN3	0.06	0.07	0.08	0.08	0.09	0.09	0.11	0.12	0.13	0.24	0.18 (3.08)	1.57

Table 6: Prediction Performance of Machine Learning Models by Using U.S. Parameters

This table reports out of sample prediction performance (R^2_{OOS}) of machine leaning models in non-U.S. developed market (Panel A) and emerging market (Panel B) by using parameters based on the training and validation sample in U.S. market and their own markets. We use 20 bond characteristics and 5 macro variables (excluding *USExGrowth*). For each market, we report time-series average $\bar{R}^2_{OOS,t}$ using market-specific parameters and U.S. parameters, and the difference of these two $\bar{R}^2_{OOS,t}$. Newey-West t-stats of $\bar{R}^2_{OOS,t}$ difference are reported in the parentheses. Machine leaning models include OLS, LASSO, ridge regression (RIDGE), elastic net (ENet), principal component analysis (PCA), partial least square (PLS), random forest (RF), gradient boosted regression trees (GBRT) and neural networks with one to five layers (NN1–NN3).

	OLS	LASSO	RIDGE	ENet	PCA	PLS	RF	GBRT	NN1	NN2	NN3
Panel A: Non-U.S. developed											
Market-Specific parameters	-3.53	2.05	1.43	2.07	1.55	1.69	2.56	2.26	1.54	1.33	2.45
U.S. parameters	-3.58	2.43	2.07	2.11	1.94	2.13	1.85	2.52	-0.24	-6.85	-15.00
Difference	0.05	-0.38	-0.65	-0.04	-0.39	-0.44	0.71	-0.26	1.78	8.18	17.45
Diff (*t*-statistics)	0.06	-1.38	-0.96	-0.19	-0.91	-1.58	0.94	-0.86	1.22	4.03	4.86
Panel B: Emerging											
Market-Specific parameters	-2.70	2.49	2.43	2.47	2.63	1.70	2.75	2.74	2.18	2.98	2.66
U.S. parameters	-7.90	0.59	0.35	0.24	-0.46	-0.67	-0.18	2.55	-2.52	-4.00	-7.94
Difference	5.19	1.90	2.08	2.23	3.09	2.37	2.93	0.19	4.70	6.98	10.60
Diff (*t*-statistics)	4.91	2.81	1.92	2.85	2.80	2.38	1.13	0.43	2.81	3.41	3.14

Table 7: Prediction Performance of Machine Learning Models by Including U.S. Factors

This table reports out of sample prediction performance (R^2_{OOS}) of machine leaning models in non-U.S. developed market (Panel A) and emerging market (Panel B) by including bonds' exposures to U.S. factors as new characteristics. The U.S. factors include MKT, SMB, HML, and DEF factors from Fama and French (1993), and bond market factor constructed in this paper. We use 20 bond characteristics, 5 macroeconomic variables and the newly added 6 factor exposures. For each market, we report time-series average $\bar{R}^2_{OOS,t}$ with and without U.S. factor exposures, and the difference of these two $\bar{R}^2_{OOS,t}$. Newey-West t-stats for $\bar{R}^2_{OOS,t}$ difference are reported in the parentheses. Machine leaning models include OLS, LASSO, ridge regression (RIDGE), elastic net (ENet), principal component analysis (PCA), partial least square (PLS), random forest (RF), gradient boosted regression trees (GBRT) and neural networks with one to five layers (NN1–NN3).

	OLS	LASSO	RIDGE	ENet	PCA	PLS	RF	GBRT	NN1	NN2	NN3
Panel A: Non-U.S. developed											
Without U.S. Factor exposures	-3.53	2.05	1.43	2.07	1.70	1.70	2.48	2.17	1.84	1.95	1.90
With U.S. Factor exposures	-3.94	2.05	1.31	2.08	1.86	1.67	2.52	2.24	1.32	1.31	1.23
Difference	0.41	0.00	0.13	-0.01	-0.16	0.04	-0.04	-0.07	0.52	0.64	0.67
Diff (*t*-statistics)	2.01	-0.18	2.02	-0.24	-0.97	0.53	-0.73	-1.60	2.10	1.41	1.38
Panel B: Emerging											
Without U.S. Factor exposures	-2.19	2.31	2.45	2.47	2.65	2.01	2.60	2.73	1.98	2.70	3.10
With U.S. Factor exposures	-2.47	2.31	2.50	2.47	2.39	2.03	2.68	2.67	2.35	2.03	2.76
Difference	0.28	0.00	-0.04	0.00	0.27	-0.02	-0.09	0.05	-0.37	0.67	0.34
Diff (*t*-statistics)	0.73	-1.06	-0.98	-	2.29	-0.20	-1.71	0.94	-1.58	3.10	3.05

Table 8: Prediction Performance of Machine Learning Models by Including Stock Characteristics

This table reports out of sample prediction performance (R^2_{OOS}) of machine leaning models in U.S. market (Panel A), non-U.S. developed market (Panel B) and emerging market (Panel C) by adding stock characteristics. We use 20 bond characteristics, 6 macro variables and 15 stock characteristics for non-U.S. developed market and emerging market, and 40 characteristics (excluding *USExGrowth*) for U.S. market. We report time-series average $\bar{R}^2_{OOS,t}$ with and without stock characteristics, and the difference of these two $\bar{R}^2_{OOS,t}$. Newey-West t-stats for $\bar{R}^2_{OOS,t}$ difference are reported in the parentheses. Machine leaning models include OLS, LASSO, ridge regression (RIDGE), elastic net (ENet), principal component analysis (PCA), partial least square (PLS), random forest (RF), gradient boosted regression trees (GBRT) and neural networks with one to five layers (NN1–NN3).

	OLS	LASSO	RIDGE	ENet	PCA	PLS	RF	GBRT	NN1	NN2	NN3
Panel A: U.S.											
Without Stock Chas	-2.43	2.77	2.46	2.60	2.31	2.29	1.66	2.44	0.95	1.74	1.66
With Stock Chas	-2.27	2.85	2.71	2.81	2.66	2.51	1.34	2.20	0.35	0.95	2.04
Difference	-0.17	-0.08	-0.25	-0.21	-0.35	-0.22	0.33	0.24	0.60	0.79	-0.38
Diff (*t*-statistics)	-1.30	-1.64	-4.86	-4.07	-0.56	-2.03	0.77	2.77	1.76	1.13	-0.52
Panel B: Non-U.S. developed											
Without Stock Chas	-3.53	2.05	1.43	2.07	1.70	1.70	2.48	2.17	1.84	1.95	1.90
With Stock Chas	-3.53	2.28	1.45	2.43	2.05	1.72	1.79	2.33	1.65	1.76	2.15
Difference	0.00	-0.23	-0.02	-0.36	-0.36	-0.02	0.69	-0.16	0.19	0.19	-0.25
Diff (*t*-statistics)	-0.04	-2.63	-0.18	-3.09	-1.66	-0.14	0.56	-0.95	0.40	0.29	-0.42
Panel B: Emerging											
Without Stock Chas	-2.19	2.31	2.45	2.47	2.65	2.01	2.60	2.73	1.98	2.70	3.10
With Stock Chas	-2.09	2.35	2.60	2.46	2.82	2.32	2.99	2.71	2.61	3.32	3.04
Difference	-0.09	-0.04	-0.14	0.01	-0.16	-0.31	-0.39	0.02	-0.63	-0.62	0.07
Diff (*t*-statistics)	-0.37	-1.31	-2.57	0.49	-1.61	-2.13	-1.59	0.38	-2.09	-1.57	0.32