Three Essays on Climate Finance and International Finance

by

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Abstract

This thesis includes three essays. In the first essay, In the first essay, we employ machine learning techniques to predict corporate bond returns globally. Utilizing a unique dataset, we identify strong predictability in international corporate bond markets. Notably, factors influencing U.S. bond returns differ significantly from those impacting non-U.S. markets, where downside risk and illiquidity play a more prominent role. Additionally, we observe variations in the degree of bond cross-country integration and bond-stock integration, with developed markets generally exhibiting higher integration than emerging markets.

The second essay investigates the impact of abnormal-temperature-related climate risk on bank loan pricing using syndicated loans from 35 countries. Our findings indicate that banks charge higher interest rates for borrowers with higher climate risk. We also find that climate risk affects loan spreads of both long-term and non-long-term loans, and this effect is more pronounced for non-long-term loans. Our cross-sectional analyses reveal that voluntary climate risk disclosures in conference calls by borrowers mitigate the impact of climate risk on loan spreads, especially when lead banks have less climate-risk-related lending experience. Furthermore, the U.S. borrowing cost for high-climate-risk borrowers decreases following SEC guidance on climate risk disclosure, while ESG disclosure requirements in 19 other countries do not alter climate risk's effect on bank loan pricing.

In the third essay, we explore the influence of climate risk disclosures in earnings conference calls on analyst forecast errors and dispersion for U.S. firms. The disclosure of physical climate risk correlates with smaller forecast errors, particularly after the SEC issued guidance. However, disclosures of regulatory and opportunity shocks related to climate change show no significant impact. Subsample analyses reveal that physical climate risk disclosures enhance forecast accuracy for industries sensitive to climate change, firms in regions affected by extreme weather events, and states with stronger beliefs in climate change. Overall, our findings suggest that physical climate risk disclosures in earnings conference calls contribute to more accurate analyst forecasts.

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Chapter 1: General Introduction

This dissertation comprises five chapters, encompassing a general introduction, three essays, and a concluding chapter. In chapter two, we apply machine learning techniques to predict corporate bond returns all over the world. With a novel dataset, we find there is strong predictability of corporate bond returns in international markets. However, the documented factors that drive bonds in the U.S. market are substantially different from factors that impact bonds in non-U.S. markets, where downside risk and illiquidity are more influential. We further find there are cross-country differences in the degree of bond cross-country integration and bond-stock integration, but these two integrations in developed markets are on average higher than in emerging markets.

In the third chapter, we explore the effect of abnormal-temperature-related climate risk on bank loan pricing. Using a sample of syndicated loans from 35 countries and jurisdictions, we find that banks charge higher interest rates for borrowers with higher climate risk. We also find that climate risk affects loan spreads of both long-term and non-long-term loans, and this effect is more pronounced for non-long-term loans. Our cross-sectional analyses reveal that voluntary climate risk disclosures in conference calls by borrowers mitigate the impact of climate risk on loan spreads, especially when lead banks have less climate-risk-related lending experience. In addition, the borrowing cost of high-climate-risk borrowers in the U.S. decreases after the SEC issued climate risk disclosure guidance. However, the ESG disclosure requirements in 19 other countries, which are not climate-risk specific, do not alter the effect of climate risk on bank loan pricing.

The third chapter examines whether climate risk disclosures in earnings conference calls affect analyst forecast errors and dispersion. Using a sample of U.S. firms from 2002 to 2019, we find that the disclosure of physical risk related to climate change is associated with smaller analyst forecast errors, while the disclosures of regulatory and opportunity shocks related to climate change have no significant effect on analyst forecast errors or dispersion. Subsample analyses reveal that the physical climate risk disclosures reduce analyst forecast errors and dispersion after the SEC provided guidance on disclosures of climate risk and opportunities, for firms in industries more sensitive to climate change, for firms located in regions that are more affected by extreme weather events and have higher disaster costs, and for firms located in states where people have stronger beliefs in climate change. Our findings suggest that physical climate risk disclosures in earnings conference calls help analysts make more accurate earnings forecasts.

Chapter 2: International Corporate Bond Returns: Uncovering Predictability Using Machine Learning

2.1. 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 focused 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 are substantially different from U.S. corporate bonds in terms of return predictors. Specifically, downside risk and illiquidity are more important in non-U.S. markets than in the U.S. market. Moreover, U.S.-based asset pricing factors provide different levels of additional predictive power to bond returns of non-U.S. countries. Bond-stock integration also varies across countries. These results have important implications for investors in terms of cross-country and cross-market diversification.

There has been a lack of research in this area, primarily because data on international corporate bonds is scarce. Only 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 determines their unique bond prices. This work is also of interest to practitioners, given that large asset management companies have started offering investment vehicles with exposure to international corporate bonds.

Our paper obtains the 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 24,450 corporate bonds issued by companies in 86 countries, from which we can observe bond returns (based on transactions or quotations), bond characteristics, and stock pricing and characteristics (if existent).[1] The bond characteristics include (i) fundamental characteristics (i.e., age, illiquidity, and credit rating); (ii) return-based characteristics (i.e., short-term reversal, momentum, and volatility); and (iii) exposure to some factors (i.e., TERM and DEF in Fama and French, 1993; BMKT, CRF, LRF, and DRF in Bai et al., 2019). To the best of our knowledge, this is the largest and most comprehensive international data set 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 the U.S. We mainly consider 21 bond characteristics. 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 monthly bond returns, and we further categorize the 10 machine learning models into linear models and non-linear models to investigate the benefit of considering nonlinearities.

We find that all the machine learning models can generate reasonable, positive R-squared both

[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).

within and outside of the U.S. market. However, there are cross-market differences in terms of the predicting performance of machine learning models due to different market structures. First, nonlinear models perform better in the U.S., while linear models generate higher R-squared in non-U.S. markets. Second, the improvement of the predictive power mainly comes from investment-grade bonds for developed markets, while the predicting performance for noninvestment-grade bonds is better in 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 9.84 to 14.04 percent per year, and an annualized Sharpe ratio varying from 1.09 to 1.56, from a long-short portfolio strategy. We find similar patterns for corporate bonds outside of the U.S., and machine learning models still generate a positive annualized Sharpe ratio ranging from 0.48 to 1.60.

In addition, we find evidence that in different groups of countries, bond returns are determined by distinct characteristics and factors. The momentum, downside risk, and illiquidity are the most influential predictors in the U.S. market, non-U.S. developed markets, and emerging markets, respectively. However, these three markets also share some similarities in terms of predicting characteristics. Downside risk, momentum, and exposures to bond risk factors (especially default beta) are among the 10 most important predicting characteristics in both U.S. and non-U.S. markets. The similar reliance on characteristics and factors of bond pricing suggests that the characteristic-return relationship could be potentially similar to some extent across these three markets. To test 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 with lower R-squared for all the machine learning models we consider. But in developed economies other than the U.S., three out of 10 U.S.-trained models experience an increase of R-squared compared to models trained by local data. These results indicate that compared with other developed economies, the characteristic-return relationship in emerging markets is much different from that in the U.S.

To further examine bond cross-market integration, we include exposure to five U.S. bond factors (BMKT, DEF, CRF, LRF, and DRF) 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. This is motivated by the typical argument of international finance literature that an asset's returns are more tied to global factors than local factors if the financial markets are more integrated (Chari and Henry 2004; Pukthuanthong and Roll, 2009). Our results show that most models generate higher R-squared after adding U.S. exposures in both the non-U.S. market and emerging market, indicating that international corporate bond markets are potentially integrated. Considering that explicit and implicit barriers lead to the cross-country differences in the degree of market integration, we further calculate the change of R-squared after adding U.S. exposures for each country and use it as a measure of country-level integration. We find that on average, non-U.S. developed countries are more integrated with the world or U.S. bond market compared to emerging countries. However, there are huge cross-country differences in the degree of market integration both within non-U.S. developed countries and emerging countries. Among developed (emerging) countries, Canada (Mexico) has the highest degree of integration, while Singapore (Russia) has the lowest. Meanwhile, the bond cross-country integration is weakly related to equity cross-country integration because bonds are held more by institutional investors.

Last, we study the bond-stock integration around the world. Specifically, we investigate whether stock characteristics can help improve cross-sectional return predictability of corporate bonds. Following Gu et al. (2020) and He et al. (2021), we further introduce 24 stock characteristics to our model, in addition to the existing bond predictors. We find that the all models experience a drop of R-squared after adding stock characteristics in the U.S. market. This indicates that the corporate bond and stock are not well integrated in the U.S., however, the predicting performance of two models in non-U.S. markets increases with extra information from the stock market. This indicates potential cross-country differences in the degree of bond-stock integration. Our country-level results show that developed countries, on average, reveal higher levels of bond-stock integration than emerging countries. Among developed (emerging) countries, Canada (Turkey) has the highest degree of bond-stock integration, while Ireland (Mexico) has the lowest. Theoretically, any country-level financial frictions that potentially lead to limits to arbitrage between bond and stock markets will affect the level of bond-stock integration.

This paper contributes to three strands of literature. First, our paper adds to the growing literature on the 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, 2023), 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 set 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 the 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; Giglio, Liao, and Xiu, 2021; Leippold, Wang, and Zhou, 2022; 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 networks 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 learning models and study corporate bond return predictability in international markets and find differences in return predictors among U.S., non-U.S. developed, and emerging markets.

Third, our paper expands extant research on the integration of international financial markets. There is a long debate on whether stocks are priced locally or globally. Most 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) are the only ones examining the integration of international corporate bond markets. Our paper differs from theirs 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 number of bond characteristics utilizing machine learning models.

Last, this paper provides insights relevant to the bond-stock integration. Theoretically, bonds and stocks should be jointly priced based on the structural credit risk model of Merton (1974). In light of this argument, numerous studies have investigated whether stock characteristics can explain bond returns (e.g., Chordia, Goyal, Nozawa, Subrahmanyam, and Tong, 2017; Choi and Kim, 2018). While these studies find several stock characteristics are related to corporate bond returns, Bali et al. (2023) fail to find significant improvement of predicting performance for bonds when adding vast stock characteristics. Thus, the corporate bond and stock markets are not well integrated. It is worth noting that all of these studies focus on the U.S. market. We extend this literature by showing that there are cross-country differences in the degree of bond-stock integration.

2.2. Data and Methodology

2.2.1. Data

We obtain daily data on the pricing of corporate bonds from IHS Markit for the period from January 2010 to December 2021. Unlike transaction-level data used in the U.S. (i.e., TRACE), transaction price is usually unavailable for corporate bonds outside of the U.S. and the price of the Markit dataset is generally based on dealers' quotes or asset pricing models such as matrix pricing. However, such prices have been viewed as the 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 features such as coupon, country of risk, amount issued, bond grades (IG or HY) and issuers, and bond features that may need complex calculations such as duration and option-adjusted spreads.[2]

To obtain the equity international security identification number (ISIN), we link the Markit data to Bloomberg through each bond's ISIN. The credit ratings are from Datastream. 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.

To filter the data, we (1) keep bonds denominated in U.S. dollars to avoid the effect of volatile exchange rates, (2) drop duplicated bonds issued under Rule 144A if their Regulation-S counterpart is already in the sample, (3) drop bonds with amounts issued less than $10,000, (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 $1,000, (7) drop bonds without ratings, (8) drop bonds without equity ISIN, and (9) keep only bonds with a fixed or zero coupon. Table 2.1 shows that our final sample includes 945,562 monthly observations for 24,450 U.S. dollar corporate bonds, issued by 2,215 companies.[3] The U.S. market, non-U.S. developed markets, and emerging markets account for 81%, 10%, and 9% of the observations, respectively.

[Insert Table 2.1 Here]

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[2] Country of risk 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.

[3] To estimate beta-related bond characteristics, we require at least 24 observations for each bond. Thus, the final sample period begins in January 2012.

Following Bai et al. (2019), the monthly 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 month t. We denote $R_{i,t}$ as bond i's return in excess of U.S. risk-free rate in month t. Returns are calculated using the last available price observation of month t ($P_{i,t}$) and the last available price observation of month $t-1$ ($P_{i,t-1}$) to allow for non-trading days.

Table 2.2 reports the time-series average of the cross-sectional bond return's distribution and characteristics. The average monthly bond return for U.S., non-U.S. developed, and emerging markets is 0.28%, 0.24%, and 0.30%, respectively. Compared to the U.S. market, the non-U.S. developed market shows lower credit risk (*Rating* 7.13 vs. 8.44), but the emerging market has higher credit risk (*Rating* 9.78 vs. 8.44). The U.S. market has the longest time to maturity, while the emerging market shows the highest illiquidity among these three markets. The emerging bond market is more likely to have extreme returns.

[Insert Table 2.2 Here]

Finally, we include 21 bond characteristics and 24 stock characteristics. Appendix A provides a detailed description of these 45 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 month for each of these three markets. For missing characteristics, we follow Bali et al. (2022) and Gu et al. (2020) to replace missing characteristics with their cross-sectional median value for each month.

2.2.2. Machine Learning Models

Following Bali et al. (2022) and Gu et al. (2020), we focus on four categories of machine learning models: penalized linear (LASSO, RIDGE, and ENet), dimension reduction (PCR and PLS), regression trees (RF, GBRT), and neural network (NN1, NN2, and NN3).[4] To investigate the potential benefit of considering nonlinearity in predicting corporate bond returns, we categorize the 10 machine learning models into linear models (including LASSO, RIDGE, ENet, PCR, and PLS) and nonlinear models (including RF, GBRT, and NN1-NN3) by following Bali, Beckmeyer, Moerke, and Weigert (2023). We average the predictions of each method included in each group and obtain the predictions for linear (L-En) models and nonlinear (N-En) models. The benefit of such a prediction combination in improving economic forecasts has been well documented in the literature (e.g., Bates and Granger, 1969; Rapach, Strauss, and Zhou 2010; Lin et al., 2018). We separate our full sample period into three disjointed time periods: (1) the first three years as a training period, T_1, to estimate the model; (2) the second two years as a validation period, T_2, to tune the hyperparameters; (3) the next five years as a test period, T_3, for out-of-sample analysis and evaluation of the model's performance. Due to limited computational resources, we retrain models yearly instead of monthly. We increase the training sample by one year and keep the validation sample the same every time we refit the model.

2.2.3. 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:

[4] The detailed description of these methods and the choice of hyperparameter can be found in Gu et al. (2020).

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

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

To calculate the relative importance of different characteristics, we follow Gu et al. (2020) and first calculate the reduction of time-series average monthly R-squared ($\bar{R}_{OOS,t}^2$) from setting all values of a given predictor to zero while keeping the remaining predictors unchanged. Variable importance is then defined as the relative reduction of $\bar{R}_{OOS}^2$. In this way, the variable importance of the characteristic with the lowest R-squared reduction is assigned to 0, while the characteristic with highest R-squared reduction has a variable importance of 1.

2.3. Empirical Results

2.3.1. Predictability of Bond Characteristics

We first examine the predicting performance of machine learning models with 21 bond characteristics. Our main purpose is to investigate the predicting performance of machine learning models in non-U.S. markets, and 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 the U.S. market.

Table 2.3 reports the out-of-sample R-squared (R_{OOS}^2) for all models. Panel A of Table 2.3 presents R_{OOS}^2 in the U.S. market. The first row reports R_{OOS}^2 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 all machine learning models achieve positive R^2_{OOS} ranging from 3.53% (GBRT) to 4.61% (NN3). The nonlinear (N-En) models make better predictions than linear (L-En) models. Compared to R^2_{OOS} for all bonds, the results in the second row indicate that all machine learning models have higher R^2_{OOS} and thus generate better predicting performance for investment-grade bonds. The better predictive performance for investment-grade bonds in the U.S. market is consistent with He et al. (2021). Panel B and Panel C of Table 2.3 report R^2_{OOS} for the non-U.S. developed market and the emerging market, respectively. Similar to the results of the U.S. market, we find that all machine learning models generate positive R^2_{OOS} for all bonds. However, the linear (L-En) models perform better than nonlinear (N-En) models in these two non-U.S. markets. Although machine learning models still achieve higher R^2_{OOS} for investment-grade bonds in the non-U.S. developed market, we observe better predicting performance for non-investment-grade bonds in emerging markets.

[Insert Table 2.3 Here]

2.3.2. Portfolio Analysis

In addition to examining the predicting power of machine learning models for corporate bond returns across markets, we further investigate the economic significance of machine learning models with portfolio analysis. Specifically, at the end of each month, we sort bonds in each of three markets into deciles based on the forecasts of bond returns for the next month, and then construct both value-weighted (amount issuance as weight) and equal-weighted long-short portfolios of corporate bonds. Table 2.4 presents equal-weighted monthly portfolio performance for all bonds (including both investment-grade and non-investment-grade bonds). We report the average monthly return of decile 1 (“Low”) to decile 10 (“High”) and denote the long-short portfolio by “High-Low”. The annualized Sharpe ratio for long-short portfolios is also presented.

Panel A of Table 2.4 reports the results in the U.S. market. A long-short trading strategy based on the forecasts of machine learning models generates an economically and statistically significant performance with average monthly return (annualized Sharpe ratios) ranging from 0.82% (1.09) to 1.17% (1.56). Consistent with our results of R^2_{OOS}, nonlinear (N-En) models achieve higher average monthly return and annualized Sharpe ratios than linear (L-En) models.

We find similar results — i.e., machine learning models having economically and statistically significant long-short performance — in the non-U.S. developed market and emerging market, as shown in Panel B and Panel C of Table 2.4. Meanwhile, linear (L-En) models are better than nonlinear (N-En) models in terms of generating higher average monthly returns and annualized Sharpe ratios. When we use value-weighted portfolios, the results are qualitatively the same, which is shown in Table 2.5.

[Insert Table 2.4 Here]

[Insert Table 2.5 Here]

2.3.3. 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 monthly R-squared ($\bar{R}^2_{OOS}$) 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 $\bar{R}^2_{OOS}$. In this way, the variable importance of the characteristic with the lowest R-squared reduction is assigned to 0, while the characteristic with the 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 the 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.

Figure 2.1 shows that bond momentum (*MOM12MBond*) is identified as the most influential predicting determinant by all machine learning models except for three nonlinear models (i.e., RF, GBRT, and NN1) in the U.S. Another version of momentum (MOM6MBond) is also instrumental in predicting bond returns, and this finding is consistent with Jostova et al. (2013). Long-term reversal (*LTR*) and downside risk (*VaR5*) are identified as the third and fourth most important predictor, respectively. We also find that some exposure measures to common factors, including *BETA_BMkt* and *BETA_DEF*, are among the 10 most important characteristics.

[Insert Figure 2.1 Here]

Figure 2.2 presents the overall rankings of characteristics in the non-U.S. developed market. There is great disagreement about the most important predictor among our machine learning models, especially among the five nonlinear models. Overall, downside risk (*VaR5*) and volatility (*VOL*) are the two most important predicting characteristics among the total 21 predictors. Similar to the results in the U.S., long-term reversal (*LTR*) is also identified as the third most important predicting characteristic for machine learning models. Two factor exposures (i.e., *BETA_DEF* and *BETA_CRF)* and momentum (*MOM12MBond*) are among the 10 most important predictors.

[Insert Figure 2.2 Here]

Figure 2.3 reports variable importance in the emerging market. Very different from the characteristic rankings in U.S. or non-U.S. markets, illiquidity (*ILLIQ*) is the most important predicting characteristic in this market. The other four most important predictors in the emerging market are momentum (*MOM12MBond* and *MOM6MBond*), downside risk (*VaR5*), and duration (*DUR*). Another notable result is that four out of six factor exposures are among the top 10 most important predictors in the emerging market. The crucial role of illiquidity in predicting corporate bond returns comes from the lowest market-level illiquidity in the emerging market. Chaieb, Errunza, and Langlois (2021) similarly find a significantly higher liquidity level premium in the emerging equity market compared to the developed equity market.

[Insert Figure 2.3 Here]

Overall, characteristics that drive bond returns in the U.S. market are substantially different from factors that impact bonds in non-U.S. markets. Downside risk and illiquidity are more influential in non-U.S. markets, while momentum is the most important predictor in the U.S. Meanwhile, there is also a measure of similarities in the return-characteristic relationship in the international corporate bond market. Specifically, downside risk, momentum, and exposure to bond risk factors (especially default beta) are crucial to predict corporate returns in both U.S. and non-U.S. markets.

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

To further compare the differences of the characteristic-return relationship among these three markets, we follow Choi, Jiang, and Zhang (2022) and 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 from characteristics of their own market. Specifically, we first estimate parameters and hyperparameters based on the training and validation sample in the 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.

Panel A of Table 2.6 presents the results for the non-U.S. developed market. The first and second rows report R_{OOS}^2 and R_{OOS}^2 differences using U.S. parameters, respectively. We find that seven out of 10 market-specific models experience a decrease of R_{OOS}^2 compared to U.S. models. Meanwhile, the results from the last two rows indicate that the increase of R_{OOS}^2 using U.S. parameters mainly comes from nonlinear (N-En) models. Panel B of Table 2.6 reports the results for the emerging market. Quite different from the results in the non-U.S. developed market, all U.S. models underperform their market-specific models, with R_{OOS}^2 difference varying from -3.48% for LASSO to -0.63% for GBRT. Overall, the results of Table 2.6 indicate that the emerging market differs more from the U.S. market in terms of return-characteristics relationship than the non-U.S. developed market.

[Insert Table 2.6 Here]

2.3.5. Integration of International Bond Markets

In the above two sections, we find that the U.S. bond market is relevant to non-U.S. markets, especially non-U.S. developed markets, with regard to variable importance and the return-characteristics relationship. In this subsection, we investigate cross-market integration for corporate bonds. Although a voluminous literature has investigated equity market integration (e.g., Bekaert and Harvey, 1995; Carrieri, Errunza, and Hogan, 2007; Bekaert, Hodrick, and Zhang, 2009; Pukthuanthong and Roll, 2009; Bekaert, Harvey, Lundblad, and Siegel, 2011; Carrieri, Chaieb, and Errunza, 2013; Akbari, Ng, and Solnik, 2020),[5] the integration of international corporate bond markets has not been well studied.

Theoretically, perfectly integrated markets mean that assets with the same risk should command identical expected returns regardless of the locations where these assets are traded. In this sense, market integration is based on the law-of-one price and requires no cross-market arbitrage opportunities (Chen and Knez, 1995). Market integration is beneficial for lowering the cost of capital, expanding investment opportunities, and finally enhancing economic growth. However, explicit barriers (i.e., legal restrictions on ownership and restrictions on institutional constraints) or implicit barriers (i.e., asymmetric information and market regulation) will affect cross-country risk-sharing and thus impact the market integration. There is extensive literature that investigates the cross-country differences in the degree of market integration (e.g., Bekaert and Harvey, 1995; Carrieri et al., 2007; Bekaert et al., 2011; Carrieri et al., 2013; Chaieb, Errunza, and Gibson, 2020).

International finance literature typically assumes that local asset returns can be explained by both local factors and global factors. If the financial markets are more integrated, an asset's returns are more tied to global factors than local factors (Chari and Henry, 2004; Pukthuanthong and Roll, 2009). In light of this argument, our measure of market integration is the change of R^2_{OOS} after incorporating global factor information. Specifically, we include bonds' exposures to five U.S. bond factors (BMKT, DEF, LRF, CRF, and DRF) as new characteristics to test whether and to what extent these predictors improve our predictions of corporate returns in non-U.S. developed and

[5] For a literature review of equity market integration refer to Akbari and Ng (2020).

emerging markets.[6] We use the U.S. market to represent global markets for two reasons: 1. the U.S. bond market accounts for 81% of our observations; 2. considering the leading role of the U.S. in international economies and financial markets, a voluminous literature has treated the U.S. market conditions as important sources of risk to global financial markets (e.g., Rapach, Strauss, and Zhou, 2013; Miranda-Agrippino and Rey, 2020).

The results from Panel A of Table 2.7 show that eight of our 10 machine learning models (excluding GBRT and NN2) generate better predicting performance (i.e., higher R^2_{OOS}) after adding the five U.S. factor exposures in the non-U.S. developed markets. The improvement is higher for linear (L-En) models compared to nonlinear (N-En) models (R^2_{OOS} difference 0.36 V.S. 0.28). Panel B of Table 2.7 reports the results for the emerging market. We find that the R^2_{OOS} of seven of our 10 machine learning models (excluding GBRT, NN3, and NN2) improves when including U.S. factor exposures. Similarly, linear (L-En) models generate a higher change of R^2_{OOS} in the emerging market. The average change of R^2_{OOS} across the 10 models after adding U.S. factors are lower for the emerging market compared to the non-U.S. developed market (0.31 V.S. 0.16). In general, the results in Table 2.7 show that information from the U.S. market can marginally improve the predicting performance for non-U.S. markets, especially non-U.S. developed markets.

[Insert Table 2.7 Here]

Considering that explicit and implicit barriers lead to the cross-country differences in the degree of market integration, we further calculate the percentage change of R^2_{OOS} after including

[6] 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 the non-U.S. developed and emerging markets.

U.S. factor exposures for each country and use it as a measure of country-level integration index.[7] Table 2.8 reports the integration for 12 developed countries and 10 emerging markets. Consistent with the results in Table 2.7, the integration of developed countries is on average higher than that of emerging markets. Due to different levels of financial development, higher integration for developed countries is found in the equity market (e.g., Akbari et al., 2020). Among developed countries, Canada has the greatest degree of integration with the world or U.S. bond market (118.39%), and Singapore has the lowest (-2.76%). As the world's third-largest economy, Japan is segmented with the international bond market with the second-lowest integration (-0.92%). Among emerging countries, Mexico has the highest degree of integration with the world or U.S. bond market (49.67%), whereas Russia has the lowest (-52.80%). China is the second-largest economy in the world but only has the fourth-lowest integration (-0.96%).

[Insert Table 2.8 Here]

Compared to equity, bonds are mainly held by institutional investors. Thus, the bond integration originating from cross-country risk sharing will be different from equity integration. Figure 2.4 plots the relationship between bond integration in this paper and equity integration constructed by Akbari et al. (2020). It shows that there is a very weak relationship between bond integration and equity integration.

[Insert Figure 2.4 Here]

2.3.6. Bond-Stock Integration

So far, we have only used bond characteristics variables to predict corporate bond returns.

[7] To reduce the noise of R^2_{OOS}, we require at least 50 bonds for each country. We average the forecasts of 10 machine learning models to estimate R^2_{OOS} to construct a unified integration measure.

Equity characteristics may generate incremental prediction power because both stocks and bonds represent claims on the same underlying assets of the firm. The structural credit risk model of Merton (1974) indicates bonds and stocks should be jointly priced or corporate bonds and stocks should be integrated if there are no financial frictions that potentially lead to limits to arbitrage. To investigate the degree of bond-stock integration, we add 24 more stock characteristics into our models and investigate the change of predicting performance.

Panel A of Table 2.9 presents how the predicting performance (i.e., R^2_{OOS}) of all of our models decreases after including stock characteristics in the U.S. Failing to find significant predicting improvement by including stock predictors across all models is consistent with the findings of He et al. (2021) and Bali et al. (2022). This indicates that bonds and stocks in the U.S. are not well integrated. We find slightly different results for non-U.S. developed and emerging markets as presented in Panel B and Panel C of Table 2.9. Some models (NN3 in non-U.S. developed markets, NN1 in emerging markets) experience improvement of R^2_{OOS} after adding stock characteristics.

[Insert Table 2.9 Here]

These results indicate that there are potential cross-country differences in the degree of bond-stock integration. We estimate the bond-stock integration for each country by measuring the change of R^2_{OOS} after adding stock characteristics. As shown in Table 2.10, bonds and stocks are more integrated in developed countries compared to emerging markets. Among developed countries, Canada has the greatest degree of bond-stock integration (114.45%), and Ireland has the lowest (-42.05%). Among emerging countries, Mexico now has the lowest degree of bond-stock integration (-166.66%), whereas Turkey has the highest (30.11%).

[Insert Table 2.10 Here]

2.4. Conclusion

A growing number of studies are devoted to the cross-section of corporate bond returns in the U.S. market. However, limited data availability prevents research in the 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 the international corporate bond market into three markets: U.S., non-U.S. developed, and emerging. We find that machine learning models generate positive out-of-sample R-squared and sizable long-short portfolio strategy profits in all of these three markets. We also find that the most important return predictors of corporate bonds in non-U.S. markets are substantially different from the U.S. market, and downside risk and illiquidity are more influential in non-U.S. markets.

We also investigate bond cross-country integration and bond-stock integration. We find that non-U.S. developed markets are more integrated to the world or the U.S. bond market compared to emerging markets. Meanwhile, there exist wide cross-country variations in the degree of bond integration, which is weakly related to equity integration. Although corporate bonds are not well integrated with stocks in the U.S., we do find extra stock characteristics improve the predicting performance of machine leaning models in some countries. Theoretically, bond cross-country integration and bond-stock integration both rely on freely investing across country and across bond-stock market in a country. Thus, any country-level frictions (i.e., explicit and implicit barriers) that stymie capital flows and limit arbitrage can potentially lead to cross-country differences in bond cross-country integration and bond-stock integration. And this is one direction for future research.

Appendix to the Chapter 2: Characteristics Descriptions

A. Corporate Bond Characteristics (21)

1. **Credit Rating (*Rating*).** We obtain bond-level rating information from Bloomberg. Credit ratings are turned to conventional linear numeric scores where a higher numerical score means higher credit risk (AAA = 1, AA+ = 2, …, C = 21). When two ratings are provided by Moody's and Fitch, the ratings are averaged.
2. **Time-to-maturity (*MAT*).** The number of years to maturity.
3. **Age (*Age*).** The number 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.
6. **Illiquidity (*ILLIQ_Bond*).** Following Amihud and Mendelson (1986), we first calculate relative bid-ask spread as ask price minus bid price, divided by the average of bid and ask prices for each day. Then, we take the mean of daily values in a month to get a monthly illiquidity proxy for each bond.
7. **Volatility (*VOL*).** We estimate historical volatility using monthly returns for the past 36 months.
8. **Skewness (*SKEW*).** We estimate historical skewness using monthly returns for the past 36 months.
9. **Kurtosis (*KURT*).** We estimate historical Kurtosis using monthly returns for the past 36 months.
10. **Downside risk (*VaR5*)**. Following Bai et al. (2019), we measure the downside risk of corporate bonds using the second lowest daily return observation over the past 36 trading months. For convenience of interpretation, we multiply the original measure by -1.
11. **Short-term reversal (*REV_Bond*).** We measure short-term reversal using bond returns in the previous month.
12. **Six-month momentum (*MOM6Bond*).** Lagged two-month to lagged six-month cumulative returns.
13. **Twelve-month momentum (*MOM12Bond*).** Lagged two-month to lagged twelve-month cumulative returns.
14. **Long-term reversal (*LTR*)**. Following Bali et al. (2021), it is defined as lagged 13-month to lagged 48-month cumulative returns.
15. **Bond market beta (*BETA_BMKT*).** Following Bali et al. (2022), we estimate the bond market beta of individual bonds on bond market excess return using the rolling sample of the past 36 months. 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.
16. **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 36 months after controlling for the bond market factor. *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.
17. **Default beta** (***BETA_DEF***). Following Fama and French (1993) and Crawford et al. (2019), we estimate the default beta of individual bonds on *DEF* factor using the rolling sample of the past 36 months after controlling for the bond market factor. *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.
18. **Downside risk beta** (***BETA_DRF***). Following Bai et al. (2019), we estimate the downside risk beta of individual bonds on downside risk factor using the rolling sample of the past 36 months after controlling for the bond market factor. Downside risk factor is the value-weighted average

return difference between the highest VaR5 portfolio (quintile 5) and the lowest VaR5 portfolio (quintile 1).[8]

19. **Credit risk beta** (***BETA_CRF***). Following Bai et al. (2019), we estimate the credit risk beta of individual bonds on credit risk factor using the rolling sample of the past 36 months after controlling for the bond market factor. Credit risk factor is the value-weighted average return difference between the highest rating portfolio (quintile 5) and the lowest rating portfolio (quintile 1).
20. **Illiquidity risk beta** (***BETA_LRF***). Following Bai et al. (2019), we estimate illiquidity risk beta of individual bonds on illiquidity risk factor using the rolling sample of the past 36 months after controlling for the bond market factor. Illiquidity risk factor is the value-weighted average return difference between the highest illiquidity portfolio (quintile 5) and the lowest illiquidity portfolio (quintile 1).
21. **Co-skewness (*COSKEW*).** Following Boyer, Mitton, and Vorkink (2010), co-skewness is estimated based on the following rolling regressions of the past 36 months:

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

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

B. Stock Characteristics (24)

Following He et al. (2021), we first construct 18 stock characteristics based on the variable definitions from Hou, Xue, and Zhang (2020).[9] We also select the six most important stock characteristics from Figure 5 of Gu et al. (2020).

B.1 Stock Characteristics from Hou et al. (2020)

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 daily stock return around the latest quarterly earnings announcement date.
3. **Revisions in analyst earnings forecasts (*RE*).** The six-month moving average of past changes in analysts' forecasts.
4. **Twelve-month momentum (*MOM12Stock*).** Lagged two-month to lagged 12-month cumulative monthly returns.
5. **Book-to-Market (*BM*).** Yearly book equity to monthly market equity.
6. **Earnings-to-rice (*EP*).** Quarterly earnings to monthly price.
7. **Cashflow-to-price (*CFP*).** Quarterly cashflow to monthly price.
8. **Sales-to-price (*SP*).** Quarterly sales to monthly price.

[8] We do not use independent sorts based on credit rating because there are a relatively small number of bonds in non-U.S. markets.

[9] Because we study the international markets, we obtain stock pricing and accounting information from Datastream rather than Compustat, as in Hou et al. (2020). We change the constructions slightly for some stock characteristics if needed.

9. **Asset Growth Rate (*AGR*).** Quarterly asset growth rate.
10. **Quarterly equity issuance (*NI*).** Quarterly equity issuance.
11. **Accruals (*ACC*).** It is measured as net income minus total operating, investing, and financing cash flow plus sales of stocks minus stock repurchases and dividends.
12. **Return on asset (*ROA*).** Quarterly return on quarterly asset.
13. **Seasonality (Ra1M).** Returns in month t - 12.
14. **Seasonality (Rn1M).** Average returns from t - 11 to t - 1.
15. **Market equity (*ME*).** Monthly market equity.
16. **Stock variance (*SVAR*).** We estimate historical volatility using daily returns for the past month.
17. **CAPM beta (*BETA*).** Following Fama and French (1993), we estimate the market beta of individual stocks on value-weighted average market excess returns using the rolling sample of the past 36 months.
18. **Short-term reversal (*REV_Stock*).** We measure short-term reversal using the stock return in the previous month.

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

1. **Six-month momentum (*MOM6Stock*).** Lagged two-month to lagged six-month cumulative monthly returns.
2. **Idiosyncratic risk (*IDIOVOL*).** Standard deviation of residuals of monthly returns on monthly value-weighted market excess returns for the past 36 months.
3. **Maximum daily return (*MAXRET*).** Maximum daily returns in a month.
4. **Amihud illiquidity (*ILLIQ_Stock*).** Monthly average of daily absolute return divided by dollar volume.
5. **Bid-ask spread (*BASPREAD*).** Monthly average of daily bid-ask spread divided by average of daily bid and ask price.
6. **Share turnover (*TURN*).** Average monthly trading volume for the most recent three months scaled by shares outstanding.

Chapter 3: Abnormal Temperatures, Climate Risk Disclosures, and Bank Loan Pricing: International Evidence

3.1. Introduction

Global warming, a remarkable aspects of climate change, causes a gradual increase in temperature. During such a long-term process, many countries reported short-term record heatwaves in recent years. For example, in 2019, the European continent experienced its hottest June in nearly a century,[10] and the record-breaking high temperatures in June 2021 forced California into a state of emergency. According to the U.S. National Weather Service, heat waves have caused more fatalities than all other weather-related natural disasters, with an average of 143 people losing their lives per year as a result of heat over the past 30 years.[11] Although global warming is an undoubted trend, there are also some extreme cold snaps. For example, the 2008 winter storms in China caused a loss of at least $21.94 billion,[12] and according to the website AccuWeather, the estimated loss resulting from the storm that hit Texas in mid-February 2021 reached as much as $130 billion. These abnormal cold weather incidents are not accidental. Johnson et al. (2018) find that occurrences of both abnormally warm weather in summer and abnormally cold weather in winter increased from 2002 to 2014.

There is a growing concern about the economic implications of abnormal temperatures. Recent studies report that abnormal temperatures negatively affect country-level economic output

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[10] https://www.marketplace.org/2019/07/11/europes-economy-wilts-in-one-of-continents-hottest-heat-waves/. Accessed June 30, 2021.
[11] https://www.weather.gov/hazstat/.
[12] *129 People Killed, 4 Missing in Winter Storms*, Xinhua News Agency, February 23, 2008, (in Chinese), http://news.sina.com.cn/c/2008-02-23/110515001984.shtml

(e.g., Burke, Hsiang, and Miguel, 2015; Dell, Jones, and Olken, 2009), reduce labor productivity (e.g., Graff-Zivin and Neidell, 2014), impact consumer demand (Addoum, Ng, and Ortiz-Bobea, 2023), directly damage or accelerate the depreciation of capital assets (Dietz et al., 2016) and negatively affect earnings (Hugon and Law, 2019; Pankratz, Bauer, and Derwall, 2023).[13] Regulators are concerned about their impact on financial stability (Carney, 2015) and banks are increasingly pressured to integrate climate-related risks into financial stability monitoring and micro-supervision (e.g., McCully, 2019; Tett, 2019). There is little empirical evidence on whether banks incorporate corporate exposure to abnormal temperatures (i.e., abnormal-temperature-related climate risk) into their bank loan pricing, and if so, whether climate risk related to abnormal temperatures has a differential impact on the pricing of non-long-term and long-term bank loans, and whether borrowers' climate risk disclosures are useful to banks when lending to high-climate risk firms. We attempt to provide a large sample of systematic empirical evidence on these important issues.

We follow Kumar, Xin, and Zhang (2019) and use the sensitivity of a firm's stock returns to temperature anomalies in its home country to measure firm-level climate risk. Specifically, our climate risk measure is an indicator variable that equals 1 if the annual average absolute climate sensitivity of a firm is in the highest quintile in its home country, and 0 otherwise. To validate our climate risk measure, we test the effect of climate risk on firm performance and credit risk. We find that higher abnormal-temperature-related climate risk is associated with lower future operating cash flows and return on assets and worse credit ratings.

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[13] See Hjort (2016) for a review of earlier papers about the effect of climate risk on financial markets and Giglio, Kelly, and Stroebel (2021) for a review of recent climate risk papers.

We examine the effect of climate risk on bank loan pricing for a sample of 22665 loan facilities from 35 countries and jurisdictions during 2000-2019. Consistent with Delis et al. (2021) and Jiang, Li, and Qian (2020), we focus on the syndicated loan market since lead banks of syndicated loans are believed to specialize in screening and monitoring their borrowers. We find that climate risk is significantly, positively associated with loan spreads. The result is economically significant. On average, loan interest spread is approximately 13.91 basis points higher for high-climate-risk borrowers than for their counterparts, which translates into an increase of USD 3.45 million in loan interest. Our baseline results are robust to non-U.S. sample and propensity-score-matched sample, and the use of an alternative measure of temperature anomaly to construct the climate risk measure. We find no significant effect of climate risk on loan spreads before 2000, indicating that climate risk was not perceived as a credit risk factor by banks until the early twenty-first century.

Prior studies find that climate risk such as sea level rise affects the pricing of long-term, not non-long-term, bank loans (Jiang, Li, and Qian, 2020; Nguyen et al., 2022). Unlike sea level rise risk that will materialize in a distant future, instances of abnormal temperatures are becoming more frequent. Therefore, we predict that banks factor climate risk related to abnormal temperatures into not only long-term but also non-long-term loans. Furthermore, the recurrent nature of abnormal temperatures enables firms to actively engage in adaptation strategies (Chen and Yang, 2019). The proactive adaptation over time implies that firms progressively develop better capacities to manage climate risk related to abnormal temperatures. Consequently, we predict a lower climate risk premium for long-term loans than for non-long-term loans. Our results are consistent with our predictions.

There has been a growing emphasis on the importance of climate risk disclosures on the pricing of climate change in both academic and industrial contexts (Krueger, Sautner, and Starks, 2020). Responding to the G20 Finance Ministers and Central Bank Governors' call, the Financial Stability Board established the Task Force on Climate-related Financial Disclosures (TCFD) in December 2015. This initiative arose from increasing demands from various stakeholders in the financial markets for decision-useful climate-related information. We also investigate whether borrowers' climate risk disclosures affect the relation between climate risk and loan spreads. On the one hand, climate risk disclosures may bring benefits to a firm by signaling its ability to measure and manage climate risk, preventing lawsuits related to climate risk, reducing information asymmetry and investors' information costs, and lowering the cost of capital (Matsumura, Prakash, and Vera-Munoz, 2014, 2022). On the other hand, disclosing climate risk could be harmful to a firm by increasing expenditures when firms adapt to climate change and revealing competitive disadvantages compared to green-marketing competitors. Using the percentage of physical climate shock bigrams appearing in the transcripts of earnings conference calls as a measure of voluntary climate risk disclosures (Sautner et al., 2023a), we find that banks charge lower interest rates for high-climate-risk borrowers if they disclose more climate risk information. This result suggests that banks reward firms disclosing more climate risk information.

We further investigate under what conditions borrowers' voluntary climate risk disclosures are more useful to banks when lending to high-climate risk firms. Lead banks may use borrowers' voluntary climate risk disclosures to a different extent, depending on their past climate-risk-lending experience. Specifically, climate risk disclosures can be more valuable to less experienced banks because they may not know how to gather and process private information related to climate risk. Our results support this conjecture. Due to lack of climate risk disclosure data for non-U.S. firms, these results are likely driven by U.S. firms.

To alleviate the concern of self-selection bias, we examine the moderating effect of disclosure policy shocks. We use the climate risk disclosure guidance initiated by the Securities and Exchange Commission (SEC) in 2010 as an exogenous shock for the U.S. and use the mandatory environmental, social and governance (ESG) disclosures as an exogenous shock for 19 other countries (Krueger et al., 2023), respectively. We find that loan spread for high-climate-risk borrowers in the U.S. significantly decreases after the 2010 SEC guidance, while the ESG disclosure requirements in the 19 countries do not affect the relation between climate risk and loan spread. Considering the facts that more U.S. firms disclose climate risk information in their SEC filings after 2010 (Kölbel et al., 2022) and ESG disclosures are not climate risk specific, these results lend further support that climate risk disclosures reduce the cost of debt financing of high-climate-risk firms.

Our paper makes three important contributions. First, it contributes to a growing literature that examines the effect of climate risk on bank loan pricing. Existing bank loan pricing literature mainly focuses on natural disasters (Correa et al., 2023; Huang et al., 2022) and long-term climate-change risk such as sea level rise (Jiang et al., 2020; Nguyen et al., 2022), drought-like conditions (Javadi and Masum, 2021), and transition risk (Delis et al., 2021; Ehlers, Packer, and de Greiff, 2022; Ho and Wong, 2022). Our study examines a different aspect of climate risk, namely, firms' exposure to abnormal temperatures, which are occurring more frequently. Analyzing a cross-country bank loan data, we provide evidence that banks perceive climate risk related to abnormal temperatures as an important driver of firms' overall credit risk, requiring a premium to address this unconventional risk factor. Importantly, our results reveal a more pronounced impact on non-long-term loans, in contrast to prior findings suggesting that sea level rise risk, which will materialize in a long run, only affects the cost of long-term loans (Jiang, Li, and Qian, 2020;

Nguyen et al., 2022). Thus, our study offers a novel perspective on the influence of climate risk, characterized by more frequent occurrences, on the costs of bank loans across various maturities. Our study also aligns with the TCFD's criticism of the misconception held by many organizations that the potential impacts of climate change are solely manifesting in the long term.[14]

Second, it expands extant research on the economic consequences of climate risk disclosures. Prior studies find that the mandatory greenhouse gas emissions disclosure requirement increases firm value (Krueger, 2015) and the U.S. financial market penalizes firms not disclosing carbon emissions (Matsumura, Prakash, and Vera-Munoz, 2014). Kölbel et al. (2021) demonstrate that voluntary physical risk disclosures decrease while transition risk disclosures increase credit default swap (CDS) spreads. We find that climate risk disclosure by firms plays a vital role in mitigating the adverse effect of climate risk on the costs of bank loans. Our findings suggest that banks, which have more information about borrowers than other market participants, reward borrowers' voluntary climate risk disclosures.

Third, our findings carry significant implications for both industry and regulators. In June 2017, the TCFD released definitive recommendations on climate-related financial disclosures, gaining widespread support from regulatory institutions globally. Since then, many countries have taken steps to formulate climate risk disclosure regulations. Notably, in October 2021, the New Zealand Government passed legislation mandating climate-related disclosures for large publicly listed companies and financial institutions, with the first phase implementation beginning on or after January 1, 2023.[15] In March 2022, the U.S. SEC unveiled a proposal to mandate extensive

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[14] https://assets.bbhub.io/company/sites/60/2020/10/FINAL-2017-TCFD-Report-11052018.pdf; accessed on November 2, 2023.

[15] https://environment.govt.nz/what-government-is-doing/areas-of-work/climate-change/mandatory-climate-related-financial-disclosures/. Accessed October 1, 2023.

climate-related risk disclosures by public companies in their SEC filings (the compliance date for large accelerated filers is fiscal year 2023 and for accelerated filers and non-accelerated filers is fiscal year 2004).[16] This underscores the timeliness and relevance of our research in addressing critical issues within the current regulatory context. Our findings can potentially encourage firms to voluntarily disclose climate risk information, thereby reducing the cost of debt financing. Furthermore, our research informs worldwide regulators of the potential benefits of mandating climate risk disclosures or promoting voluntary disclosures of climate risks.

3.2. Literature Review and Hypothesis Development

To alleviate information asymmetry between borrowers and lenders, banks often charge higher interest rates or implement specific loan terms to safeguard their interests. Prior studies indicate that information risk (e.g., Bharath, Sunder, and Sunder, 2008; Costello and Wittenberg-Moerman, 2011; Hsieh et al., 2019; Graham, Li, and Qiu, 2008; Kim, Song, and Stratopoulos, 2018), agency risk (e.g., Chava, Livdan, and Purnanandam, 2009; Ge, Kim, and Song, 2012; Lin et al., 2011, 2012), legal institutions (e.g., Bae and Goyal, 2009; Ge et al., 2021; Ge et al., 2016; Qian and Strahan, 2007), corporate globalization (Li, Qiu, and Wan, 2011), corporate culture of banks (Nguyen, Nguyen, and Sila, 2019), and banks' choice of capital requirements (Mascia, 2023) affect bank loan contracting terms.

Climate risk related to abnormal temperatures can affect corporate profit and, consequently, credit risk, through various channels. First, abnormal temperatures could negatively impact corporate output. Many studies find a negative association between abnormal temperatures and firm profit in agriculture (e.g., Burke and Emerick, 2016; Fisher et al., 2012). Burke, Hsiang, and

[16] https://www.sec.gov/files/33-11042-fact-sheet.pdf. Accessed April 2, 2022.

Miguel (2015) estimate that global incomes will decrease by roughly 23% by 2100 if the adaptation to global warming remains unchanged. They also show that the overall economic productivity declines significantly at extremely high temperatures. Focusing on the 12 countries of the Americas, Dell, Jones, and Olken (2009) find that there is a significant negative cross-country relationship between temperature and income, and such an effect even exists within states. Second, labor productivity may decrease on days with abnormal temperatures. Graff-Zivin and Neidell (2014) find that labor supply in outdoor sectors (e.g., agriculture, forestry, construction, mining, transportation, and manufacturing) declines in warm days. Third, abnormal temperatures can cause direct damage on or accelerated depreciation of capital assets (Dietz et al., 2016). Fourth, in addition to the supply, consumer demand could be negatively affected by abnormal temperatures. For example, Addoum, Ng, and Ortiz-Bobea. (2023) investigate the impact of extreme temperatures on firm earnings and find that most of the temperature-sensitive industries are in consumer sectors. Hugon and Law (2019) and Pankratz et al. (2023) also find that extreme temperatures negatively affect firms' earnings. Some firms are more sensitive to abnormal temperatures than others. Firms with higher climate risk will be more affected by abnormal temperatures and thus have higher credit risk.

Recent studies provide empirical evidence that banks price various aspects of risk related to climate change. Specifically, Jiang, Li, and Qian (2020) find that in the U.S., the cost of long-term bank loans is higher for firms located in counties with higher sea level rise risk, especially for firms that have difficulty adjusting to rising sea levels. Similarly, Nguyen et al. (2022) indicate that mortgage lenders charge higher interest rates for long-term mortgages on residential properties exposed to a greater risk of sea level rise. Javadi and Masum (2021) report that U.S. firms located in states with higher drought intensity have higher cost of borrowing. Prior studies focusing on transition risk find that banks price the risk of stranded fossil fuel reserves due to the transition to a low-carbon economy (Delis et al., 2021), and after the Paris Agreement, banks charge a risk premium for carbon risk (Ehlers, Packer, and de Greiff, 2022; Ho and Wong, 2022). Correa et al. (2023) find that following a natural disaster such as a hurricane landfall elsewhere, banks charge higher loan spreads for borrowers with operations in disaster-prone areas, but not directly affected by a specific event. Similarly, Huang et al. (2022) report that firms exposed to climate hazard events pay higher interest.

With global climate change, abnormal temperatures occur more frequently than before (e.g., Johnson et al., 2018). As firms with higher climate risk may suffer more potential losses in abnormal weather, we expect banks to charge higher interest rates when lending to borrowers with higher abnormal-temperature-related climate risk. Thus, we develop the following hypothesis:

H_1: Firms with higher abnormal-temperature-related climate risk are charged higher loan spreads.

3.3. Research Design, Data and Sample

3.3.1. The measure of climate risk

To measure climate risk related to abnormal temperatures, several studies use the temperature variations surrounding firms' headquarters (Hugon and Law, 2019; Pankratz et al., 2023). While intuitive, such a measure has two significant weaknesses. First, it does not incorporate the effect of abnormal temperatures on firms' establishments across the country. Although Addoum et al. (2023) construct an establishment-level temperature exposure in the U.S., we lack information on firms' establishment-level activities in a global context. Second, this measure assumes a uniform impact of abnormal temperatures on each industry and each firm. However, extreme temperatures may affect firms' financial performance differently across industries (Addoum, Ng, and Ortiz-Bobea, 2023). Even for firms in the same industry, abnormal temperatures may result in different extents of economic losses due to the operational differences among firms and firms' adaptation to climate change (Engle et al., 2020). In this paper, we extract firm-level climate risk from stock markets because investors react to extreme temperatures and firms' exposures to extreme temperatures are priced in equity markets (Bansal, Kiku, and Ochoa, 2019; Choi, Gao, and Jiang, 2020).

In asset pricing, beta, i.e., the sensitivity of stock return to a risk factor, is a traditional way to define a firm's exposure to that risk (e.g., Bali, Brown, and Tang, 2017). Following Kumar, Xin, and Zhang (2019), we use the sensitivity of stock return to temperature anomalies to measure a firm's exposure to climate risk. Consistent with Kumar, Xin, and Zhang (2019) and Bansal, Kiku, and Ochoa (2019), monthly temperature anomalies are measured by the deviations from the average temperature of a particular month over the 1951-1980 period. For each stock and each month, we estimate the temperature beta by running the following monthly rolling regression:

$$r_{i,t,C}^{e} = a_i + \beta_{i,TEM}\Delta TEM_{t,C} + \beta_{i,m}MKT_{t,C} + \beta_{i,s}SMB_{t,C} + \beta_{i,h}HML_{t,C} + \varepsilon_{i,t}\ , \qquad (3)$$

where $r_{i,t}^{e}$ is the excess stock return of firm *i* for month *t* in country *C*; $\Delta TEM_{t,C} = TEM_{t,C,T} - TEM_{t,C,1951-1980}$, is the temperature anomaly for month *t* in year *T* in country *C*; and MKT_t, SMB_t, HML_t are the three pricing factor in month *t* collected from French's data library. Consistent with Hou, Karolyi, and Kho (2011), the rolling window is 36 months (at least 12 months of available data).

$\beta_{i,TEM}$ in Eq. (1) captures the return sensitivity to temperature anomaly for stock i in month t. A stock with positive (negative) $\beta_{i,TEM}$ earns higher average returns during abnormal high (low) temperature periods but has lower average returns during abnormal low (high) temperature periods. Since the frequencies of cold extremes and warm extremes increase, the returns of stocks with a higher absolute value of $\beta_{i,TEM}$ ($|\beta_{i,TEM}|$) will be highly influenced by abnormally high or low temperatures. Thus, firms with higher $|\beta_{i,TEM}|$ have higher climate risk because stock returns reveal the earning expectations. Therefore, following Kumar, Xin, and Zhang (2019), we first calculate $|\beta_{i,TEM}|$ for each rolling window for each firm. Next, for each year, we compute the annual average $|\beta_{i,TEM}|$ for each firm and use it to sort firms in country C into five groups. We then generate our measure of corporate exposure to extreme temperatures, *ClimateRisk*, an indicator variable that equals 1 if the annual average $|\beta_{i,TEM}|$ of a firm is in the highest quintile in year t and country C, and 0 otherwise. Kumar et al. (2019) find this climate risk measure predicts lower firm profits.

3.3.2. Research design

To investigate the impact of abnormal-temperature-related climate risk on the cost of bank loans, we estimate the following regression model:

$$LnSpread_{i,t} = \phi(ClimateRisk_{i,t-1}, X_{i,t-1}, \text{IndustryEffects}, \text{YearEffects}, \text{CountryEffects}) \quad (4)$$

In Eq. (2), the dependent variable is measured by the natural logarithm of the all-in-drawn spread (*LnSpread*). *ClimateRisk* is described in Section 3.1. H_1 predicts that the coefficient of *ClimateRisk* to be positive. X represents three sets of control variables that may affect loan spreads (Lin et al. 2011; Deng, Willis, and Xu, 2014): (1) loan-specific variables including size, maturity, purpose, type, total covenants, the use of collaterals, and the use of performance pricing provisions; (2) borrower characteristics including firm size, profitability, leverage, tangibility, market-to-book ratio, cash flow volatility, modified Altman's (1968) Z-score, and credit rating; and (3) macroeconomic condition captured by the annual GDP growth rate. We also control for industry, country, year, and bank fixed effects. When we control for bank fixed effects, we use the lead bank with the largest share of the loan amount. The appendix provides variable definitions.

Eq. (2) is estimated at the facility level (Lin et al., 2011; Deng, Willis, and Xu, 2014). The standard errors of the estimated coefficients are adjusted for firm-level clustering.

3.3.3. Data sources and sample

We extract bank loan data from Dealscan. Countries with less than 10 stocks are excluded. The accounting data and stock returns are obtained from Compustat and Datastream, respectively. We use the updated version of the Compustat-Dealscan link file provided by Chava and Roberts (2008) to merge accounting and loan data. We use the monthly exchange rate data obtained from Compustat to convert foreign currencies to U.S. dollars, so all financial data are measured in U.S. dollars. We exclude financial and utility industries since they are subject to different regulations. Following Ince and Porter (2006) and Hou, Karolyi, and Kho (2011), we apply the following filters: First, only common stocks are selected. Second, any returns above 300% and then reversed within one month are set to missing, that is, if R_t or R_{t-1} is greater than 300% and $(1 + R_t)(1 + R_{t-1}) - 1$ is less than 50%, both R_t and R_{t-1} are set to missing. Third, stock returns falling outside of the 0.1% to 99.9% range in each country are set to missing. Fourth, to be included in the sample, a stock must have a minimum price of $1 at the end of the previous month. Fifth, we focus on firms listed in domestic markets and exclude cross-listing firms.

We obtain temperature data from Climate Research Unit (CRU) Country (CY) database, which provides monthly, seasonal, and annual country averages for ten weather-related variables for 292 countries or jurisdictions.[17] To construct the climate risk measure, we use the mean temperature and the factor data from French's data library.[18] After merging data from these sources, our final sample includes 22665 facilities from 35 countries and jurisdictions (covering 43 Fama-French industries) from 2000 to 2019. Our sample starts from 2000 because climate change was not widely recognized until the new millennium (Choi, Gao, and Jiang, 2020). In line with Deng, Willis, and Xu (2014), we winsorize all continuous variables at the 1% and 99% levels.

3.3.4. Descriptive statistics and correlation matrix

Panel A of Table 3.1 presents the summary statistics for the full sample. The mean *LnSpread* is 5.06 for loans to firms with low climate risk and 5.42 for loans to firms with high climate risk. This mean difference is significant (*t*-statistics = -20.08), suggesting that, unconditionally, on average, firms with high climate risk have higher borrowing costs. Panel A also shows that banks are more likely to use collateral for borrowers with high climate risk and the size of loans to these borrowers is smaller. Firms with high climate risk are smaller, and have lower profitability, higher leverage, and lower market-to-book ratio. The values of our variables align with those reported in the literature. For example, the mean spread (210.28) in our sample (including U.S. firms and non-U.S. firms) is slightly higher than that reported in U.S.-based studies, such as 177.26 in Javadi and Masum (2021) and 185.65 in Jiang, Li, and Qian (2020), yet lower than the mean spread of 280.66 reported in the international study by Delis et al. (2019). The variation in mean spread is not surprising given that these studies cover different countries and sample periods. Similarly, our

[17] https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.05/crucy.2103081329.v4.05/countries/. Harris et al. (2020) provide more information about this dataset.
[18] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

mean *FirmSize* of 7.82 is comparable to 7.03 reported in Javadi and Masum (2021) and 8.72 reported in Delis et al. (2019).

Panel B of Table 3.1 details the distribution of observations and key summary statistics across countries. The U.S. observations represent 80.35% of our sample, followed by the U.K. (4.57%). The variation in the mean value of *ClimateRisk* across countries is a byproduct of our construction methodology. We first construct the climate risk variable by aggregating data from all stocks within a specific country, ensuring a sufficient sample size for categorizing them into five quintiles. We then merge the climate risk data with bank loan data. Consequently, differences in stock availability for merging climate risk with bank loan data contribute to varying degrees of sample loss, explaining the observed variations in mean *ClimateRisk* across countries.

[Insert Table 3.1 Here]

Table 3.2 reports the Pearson correlation matrix. The correlations between our climate risk measure and most variables are significant at conventional levels. Notably, the loan variables exhibit stronger correlations, ranging from -0.34 to 0.64, consistent with the findings reported by Costello and Wittenberg-Moerman (2011) and Kim, Song, and Wang (2017). The Variance Inflation Factors among the variables (not tabulated) are well below 2.5, suggesting a low likelihood of multicollinearity.

[Insert Table 3.2 Here]

3.4. Baseline Results

3.4.1. Climate risk, firm performance, and credit risk

To validate our climate risk measure, we examine the effects of climate risk on firm performance and credit risk. Following Huang, Kerstein, and Wang (2018) and Ozkan, Temiz, and Yildiz (202), we use return-on-assets (*ROA*) and cash flows from operations (*CFO*) in year *t*+1 to measure future financial performance. *ROA* is pre-tax income scaled by total assets, and *CFO* is cash flows from operations scaled by total assets. Credit ratings in year *t*+1 from S&P, Moody's, or Fitch are used to measure firms' credit risk, and ratings are converted to conventional linear numeric scores (e.g., 1 for a AAA rating, 2 for AA+, ..., and 22 for D). This *Rating* variable is set to 23 for firms not rated by any of these three agencies. Therefore, higher *Rating* implies higher credit risk.

Table 3.3 report the results. The significantly negative coefficients of *ClimateRisk* in columns (1) and (2) suggest that firms with high climate risk have worse future financial performance. The result is economically significant. Given that the average *ROA* at the firm level is 5.1% (not reported in Table 3.1), the coefficient of -0.025 for *ClimateRisk* in column (2) suggests that the average *ROA* of firms with high climate risk is 2.6% (=5.1% - 2.5%), significantly smaller than the overall firm-level average (5.1%). As reported in column (3), high-climate-risk firms are associated with higher future credit ratings (i.e., higher credit risk). These results indicate that *ClimateRisk* can significantly and negatively forecast firms' future financial performance and credit risk, and thus is a validate climate risk measure.

[Insert Table 3.3 Here]

3.4.2. Climate change risk and bank loan pricing

Table 3.4 reports the baseline results of testing the effect of climate risk on bank loan pricing. Column (1) does not include control variables, column (2) adds firm and macro variables, and column (3) further controls for loan specific variables. Consistent with H_1, the coefficients of *ClimateRisk* in columns (1) to (3) are consistently positive and significant. These results indicate that banks charge higher interest rates to borrowers with high abnormal-temperature-related climate risk. The finding still holds after including bank fixed effects in column (4).

Our results are economically significant as well. For example, in column (4) of Table 3.4, the coefficient of *ClimateRisk* (0.064) indicates that, on average, the loan spread is about 6.61% higher for firms with high climate risk than for firms with low climate risk.[19] Given the average loan spread in our sample is 210.28 basis points, it suggests that high climate risk increases loan spread by approximately 13.91 basis points (210.28 ×6.61% =13.91), which is higher than a carbon risk premium since the 2016 Paris Agreement of 3 to 4 basis points reported by Ehlers, Packer, and de Greiff (2022) and the sea level rise risk premium of 7.5 basis points reported by Nguyen et al. (2022). Given the average loan amount of USD 565.48 million and the average maturity of 52.56 months in our sample, a 13.91 basis point increase translates into an increase of USD 3.45 million (565.48 × 13.91 /10000 × 52.56 /12) in financing cost.

[Insert Table 3.4 Here]

[19] As the dependent variable is the natural logarithm of loan spread, the percentage change in loan spread is calculated as ($e^{0.064} - 1$).

3.4.3. Robustness and "Placebo" tests

3.4.3.1. Non-U.S. sample

As shown in Panel B of Table 3.1, 80.35% of our sample is from the U.S. To address the concern that our baseline results may be disproportionately influenced by U.S. firms, we conduct analyses specifically for non-U.S. sample. In Panel A of Table 3.5, a significant effect of climate risk on borrowing costs is consistently observed in both columns, both before and after adding bank fixed effects. The magnitude of the coefficient on *ClimateRisk* more than doubles the coefficient observed in Table 3.4 (0.149 vs. 0.064) after controlling for bank fixed effects, which represents a 16% (i.e., $e^{0.149} - 1=16\%$) increase in loan spread for the non-U.S. sample. The higher impact in non-U.S. countries may be attributable to the limited ability of banks to diversify risk in these smaller or less-developed markets.

3.4.3.2. Propensity-score-matched (PSM) sample

To alleviate the concern that our results may be driven by inherent differences between firms with high and low climate risk, we construct a PSM sample. First, we compute the propensity score after running a probit regression of the probability of *ClimateRisk* =1 on the firm-level control variables as specified in Eq. (2). We also control for industry, country, and year effects in this stage. Next, for each firm-year observation in the high climate risk group, we conduct a one-on-one match without replacement using the closest propensity score, and identify 982 matched firm-year observations in the low climate risk group. The PSM sample is comprised of 1964 (i.e., 982×2) paired firm-years and 3404 loan facilities. Panel B of Table 3.5 shows that the positive association between *ClimateRisk* and *LnSpread* still holds for the PSM sample.

3.4.3.3. Alternative temperature anomaly benchmark

To measure temperature anomaly, we use the average temperature each month during 1951-1980 in each country as a benchmark. This consistent benchmark window ensures the comparability of the monthly temperature anomaly across years. However, given that our climate risk measure is based on investors' reactions to temperature anomaly, a potential concern is that people's perception of temperature anomaly may evolve over time, rendering the 1951-1980 benchmark window potentially outdated. To alleviate this concern, we generate a new measure of monthly temperature anomaly based on the deviation of the temperature in month *t* of year *T* in country *C* from the average temperature for that month over a rolling window of past 30 years (i.e., *T*-31 to *T*-1) in country *C* and then re-estimate Eq. (1) to construct the climate risk measure. Panel C of Table 3.5 shows that the significant effect of climate risk on borrowing cost still holds with the new climate risk measure.

3.4.3.4. "Placebo" test

Climate change was not widely recognized as a global crisis until the beginning of the twenty-first century (Choi, Gao, and Jiang, 2020). Following Choi, Gao, and Jiang (2020), we use the period 1992−1999 to conduct a "placebo" test, anticipating no impact of climate risk on bank loan pricing in this period. As shown in Panel D of Table 3.5, we do not find significant effect of climate risk on the cost of bank loans, which is consistent with prior findings that various aspects of climate risk have only been priced by investors or debt holders in recent years (Delis et al., 2021; Painter, 2020). Our results are also related to Baldauf, Garlappi, and Yannelis (2020), who show that the price of houses projected to be underwater is discounted only when neighborhoods believe in climate change. Despite the persistent negative effects of abnormal temperatures on firm performance, these results suggest that it did not become a newly priced risk factor until the early twenty-first century (Kölbel et al., 2022).

[Insert Table 3.5 Here]

3.5. Loan maturity and climate risk

Our climate risk measure is linked to sensitivity to abnormal temperatures. Notably, instances of abnormal temperatures have been observed in the past and are becoming more frequent, so this aspect of climate risk is distinct from other climate risks such as sea level rise risk that are solely prospective in the long run (Jiang et al., 2020; Nguyen et al., 2022). This temporal distinction is crucial as it underscores the recurrent nature of abnormal temperatures, allowing firms to actively engage in adaptation strategies. Repeated exposure to abnormal temperatures enables firms to mitigate the negative effects on their output (Chen and Yang, 2019). This proactive adaptation over time implies that firms are better equipped to deal with abnormal-temperature-related climate risk in the long run. Thus, we predict that banks are likely to charge a lower climate risk premium for long-term loans than for non-long-term loans.

To investigate potential differential effects of climate risk on the cost of bank loans with different maturities, we add an interaction term, *ClimateRisk*LnMaturity*, to Eq. (2). As reported in Table 3.6, the coefficient of *ClimateRisk* is positive and significant, while the interaction term is negative and significant in both columns without (column 1) and with bank fixed effects (column 2). In addition, the magnitude of the coefficient of *ClimateRisk* is much larger than that of the interaction term. The results indicate that climate risk affects the pricing of both non-long-term and long-term loans, but the effect is more pronounced for non-long-term loans.

We also partition our sample to non-long-term (with maturity of five years or less) and long-term loans (with maturity of longer than five years) and estimate Eq. (2) for these two subsamples. The results (not tabulated for brevity) indicate that the coefficient of *ClimateRisk* is positive and significant for both long-term and non-long-term loans, but the impact is more pronounced for non-long-term loans, which aligns with interaction results reported in Table 3.6.

[Insert Table 3.6 Here]

3.6. The moderating effect of climate risk disclosures

3.6.1. Borrowers' voluntary climate risk disclosures

The availability of climate risk information is crucial for market participants to assess and price climate risk (Krueger, Sautner, and Starks, 2020). In this section, we investigate the effect of climate risk disclosures on the relation between climate risk and bank loan pricing. On the one hand, climate risk disclosures may benefit the firm by lowering the cost of capital, avoiding lawsuits related to climate risk, signaling its ability to measure and manage climate risk, and reducing information asymmetry and investor information costs (Matsumura et al., 2014; Krueger 2015). Huang et al. (2022) indicate that firms' climate risk management (e.g., corporate climate strategy, specific or integrated process to cope with climate change, climate policy involvement, etc.) can mitigate banks' concerns about firms' exposure to climate hazard events. Therefore, banks will charge a lower climate risk premium to firms disclosing more climate risk information. On the other hand, disclosing climate risk could be harmful to a firm, because of the potential for increasing expenditures to adapt to climate change, divulging a competitive disadvantage compared to green-marketing competitors, revealing a novel risk factor, and increasing investors' risk perception (Matsumura, Prakash, and Vera-Munoz, 2022; Kölbel et al. 2022). In this sense, banks are more likely to charge a higher climate risk premium to firms with more climate risk disclosures.

To test whether the borrowers' voluntary climate risk disclosures affect the relation between climate risk and loan spread, we obtain the annual climate risk disclosures from Sautner et al. (2023a), who gauge the proportion of discussions dedicated to climate change-related topics and calculate the percentage of climate change bigrams appearing in the transcripts of earnings conference calls. One may consider the climate risk information disclosed in conference calls as a measure of climate risk itself. Nevertheless, as Sautner et al. (2023a) state in their paper, these measures capture "the attention that financial analysts and management allocate to climate change topics at a specific moment in time", so these exposures are not directly categorized as risk. In addition, from an accounting perspective, any information disclosed by firms through 10-K filings or conference calls represents part of their disclosures. While these disclosures have the potential to influence market participants' risk perceptions, they may not necessarily result in increased risk perceptions among market participants, but instead, could mitigate information asymmetry. Such disclosures could resolve known risk factors and signaling corporate capacities to cope with climate risk. For instance, Kölbel et al. (2022) find that physical risk disclosure is associated with a decrease in CDS spreads, and Bao and Datta (2014) observe that five out of eight types of disclosed risks decrease investors' risk perceptions. There are also numerous studies indicating that conference call disclosures reduce information asymmetry (e.g., Brown, Hillegeist, and Lo, 2004; Bushee, Gow, and Taylor, 2018). Hence, it is an open question whether climate risk disclosures in conference calls increase banks' risk perception and thus require a higher climate risk premium or alleviates information asymmetry and thus require a lower climate risk premium.

Sautner et al. (2023a) construct several climate change exposure measures to capture opportunities (e.g., new energy, wind energy, etc.), regulatory shocks (e.g., carbon tax, reduce emission, etc.), and physical shocks (e.g., global warming, snow ice, etc.) related to climate change, respectively. Since our climate risk measure focuses on the risk arising from abnormal temperatures, which is closely related to physical climate exposure ($CCExposure^{Phy}$) in Sautner et al. (2023a), we use $CCExposure^{Phy}$ to measure climate risk disclosures.[20] We multiply $CCExposure^{Phy}$ by 100000 (labelled as *ClimateRiskDisclosure*) because $CCExposure^{Phy}$ is too small to compare the disclosure difference between firms with high versus low climate risk. We add this variable and its interaction term with *ClimateRisk* to Eq. (2) to test whether the effect of climate risk on loan pricing is contingent on the extent of borrowers' climate risk disclosures.

Panel A of Table 3.7 reports the results for our full sample. As shown in column (1), the main effect of *ClimateRisk* on loan spread is positive and significant, consistent with our baseline results; in addition, the coefficients of the interaction term, *ClimateRisk*ClimateRiskDisclosure*, is negative and significant, suggesting that for borrowers with higher climate risk, banks tend to charge lower interest if they disclose more climate risk information. The results are similar in column (2) after controlling for bank fixed effects. The results are economically significant. The coefficients of *ClimateRisk* and *ClimateRisk*ClimateRiskDisclosure* suggest that a one-unit increase in voluntary climate risk disclosure results in a corresponding decrease of 0.013 units in the impact of *ClimateRisk* on *LnSpread*. This reduction constitutes a substantial 18% decrease in the overall effect (0.013/0.072=18%). As shown in Panel A of Table 3.1, the mean value and

[20] Risk is the "combination of the probability [of occurrence] of a certain event and its negative consequences" (UNISDR, 2009). When we replace *ClimateRisk* with $CCExposure^{Phy}$ and re-estimate our baseline regressions, we find that $CCExposure^{Phy}$ significantly predicts higher *ROA*, and has a negative but insignificant effect on credit rating and loan spread. These results suggest that $CCExposure^{Phy}$ is unlikely to be a risk measure for banks.

standard deviation of *ClimateRiskDisclosure* are 1.35 and 9.22, respectively, so the economic significance of the moderating effect becomes more pronounced when examining changes equivalent to the mean value or one standard deviation of *ClimateRiskDisclosure*.

As the Sautner et al. (2023a) measure is based on transcripts of conference calls conducted in English, the number of observations from non-U.S. countries drops significantly for this analysis. Nevertheless, the moderating effect of climate risk disclosures holds for both the U.S. and non-U.S. samples, as shown in Panel B of Table 3.7.

Overall, our results indicate that climate risk disclosure moderates the effect of climate risk on loan spreads. This may be due to reduced information asymmetry when borrowers voluntarily disclose more climate risk information to signal their ability to adapt to and manage such risk. These results are consistent with Krueger (2015), Matsumura, Prakash, and Vera-Munoz (2014), and Matsumura, Prakash, and Vera-Munoz (2022), who find that the financial market rewards firms disclosing climate risk information.

[Insert Table 3.7 Here]

3.6.2. Which banks reward firms' climate risk disclosures?

In addition to climate risk disclosures made by borrowers, banks can gather borrowers' climate risk information through repeat lending to borrowers with different levels of climate risk. Lead banks with more climate-risk-related lending experience may less value firms' public climate risk disclosures if they can rely on their expertise developed from their own past climate-risk-related lending experience to collect and analyze private information efficiently. In contrast, lead banks with less climate-risk-related lending experience may not know how to gather and process private information related to climate risk, so firms' climate risk disclosures induced by analysts in conference calls are more valuable to these banks. Thus, we expect the moderating effect of firms' climate risk disclosures to be stronger when lead banks have less past climate risk experience.

To shed light on this issue, following Jiang, Li, and Qian (2020), we first construct lead banks' past experience with high-climate-risk borrowers as the sum of weighted climate risk across the loans that each lead bank has made so far. Specifically, for each year *t*,

$$Each\ Lead\ bank's\ climate\ experience_t = \frac{\sum_{j\leq t} loan\ amount_j \times Climate\ risk_j}{\sum_{j\leq t} loan\ amount_j}$$

We then generate an indictor variable, *LeadBankExperience*, that equals 1 if the sum of each lead bank's climate risk experience for a loan facility is above the median, and 0 otherwise. We test the moderating effect of climate risk disclosures for subsamples borrowed from lead banks with more versus less past climate-risk-related lending experience.

The results in Table 3.8 show that the moderating effect of climate risk disclosures on the relation between climate risk and loan spread is significant in the low-experience subsample only (columns (3) and (4)), consistent with our prediction. Due to the limited availability of climate risk disclosure data for non-U.S. firms, only a small number of observations from non-U.S. firms are included in the sample for this analysis. The results need to be interpreted with caution since these results may be primarily driven by U.S. firms.[21]

[21] We also conduct separate analyses for U.S. and non-U.S. samples (results not tabulated for brevity). The U.S. sample results are consistent with those of the full sample. Regarding the non-U.S. sample, the limited availability of climate risk disclosure data for non-U.S. firms results in a small sample size, and there is inadequate variation in the interaction term *ClimateRisk*ClimateRiskDisclosure*, particularly in the high-experience group. Consequently, no coefficient is loaded for this interaction term for the high-experience group. However, it is noteworthy that the coefficient of this interaction term remains significantly negative for the low-experience group of the non-U.S. sample. Due to the scarcity of climate risk disclosure data, the findings for non-U.S. firms are inconclusive.

[Insert Table 3.8 Here]

3.6.3. Country-level climate risk disclosure policy shock

According to Sautner et al. (2023a), climate information from conference calls is much less susceptible to "greenwashing" by management compared to other information sources such as annual reports and press releases. This is because financial analysts and other market participants can ask climate risk related probing questions even if the management evades climate risk topics or overstates their achievements. In this sense, there is little concern of self-selection bias when we use the climate risk disclosures in conference calls. However, to further alleviate such concern, we examine the moderating effect of disclosure policy shocks.

In January 2010, the U.S. SEC clarified how existing SEC disclosure rules may apply to climate change matters and provided guidance on disclosures of climate change risks. The overall climate risk information disclosed by firms is more available after 2010 (Kölbel et al., 2022). Thus, for the U.S. firms, we use the 2010 SEC climate risk disclosure policy as an exogenous shock and generate an indicator variable, *PostYear2010*, that equals 1 for loan facilities initiated after 2010, and 0 otherwise. We then add *PostYear2010* and its interaction term with *ClimateRisk* to Eq. (2). For non-U.S. countries, we use the introduction of the mandatory ESG disclosures in 19 countries or jurisdictions as an exogenous shock (Krueger et al., 2023) and construct an indicator variable, *MandataryESG*, that equals 1 if a loan facility starts after the borrower's home country introduced mandatory ESG disclosure, and 0 otherwise.[22] We add *MandataryESG* and its interaction term with *ClimateRisk* to Eq. (2) for firms in these countries.

[22] The 19 countries or jurisdictions and their policy implementation year in our sample are as follows: Australia in 2003, Austria in 2016, Chile in 2015, China in 2008, France in 2003, Greece in 2006, Hong Kong in 2016, India in 2015, Italy in 2016, Malaysia in 2007, the Netherlands in 2016, Norway in 2013, Singapore in 2016, South Africa in

Panels A and B of Table 3.9 report the regression results for the U.S. and non-U.S. samples, respectively. In Panel A, the effect of *ClimateRisk* on loan spread is generally consistent with our baseline results. The significant, negative coefficient of *ClimateRisk*∗*PostYear2010* in column (1) indicates that banks charge a lower climate risk premium after the issuance of country-level disclosure policies that induce more climate risk disclosures. The results remain similar when we control for bank fixed effects in column (2).

For non-U.S. sample (Panel B of Table 9), the main effect of climate risk on loan spread still holds. The insignificant coefficients of *ClimateRisk*∗*MandataryESG* indicate that mandatory ESG disclosures have no significant moderating effect on the relation between climate risk and loan pricing. One potential reason is that mandatory ESG disclosures do not necessarily lead to more climate risk disclosures because the environment component of ESG is not climate-risk specific.

[Insert Table 3.9 Here]

3.7. Conclusion

In this paper, we examine the effects of abnormal-temperature-related climate risk on bank loan pricing. We find that banks charge higher interest rates when lending to firms with high climate risk. We also find that abnormal-temperature-related climate risk affects loan spreads of both long-term and non-long-term loans, but this effect is more pronounced for non-long-term loans.

We also test whether climate risk disclosure in conference calls moderates the relation between climate risk and loan spreads. Our results indicate that high-climate-risk firms receive lower

2010, Spain in 2012, Switzerland and Thailand in 2014, Turkey in 2014, and the United Kingdom in 2013. See Krueger et al. (2023) for the full list of 25 countries that introduced the mandatory ESG disclosures.

interest rates if they disclose more climate risk information, and this effect concentrates in banks with less past climate-risk-related lending experience. Furthermore, we find that, in the U.S., the effect of climate risk on bank loan pricing decreases after the SEC issued disclosure guidance to induce more climate risk disclosures; in contrast, the ESG disclosure requirements in 19 other countries, which are not climate-risk specific, do not show moderating effect on the relation between climate risk and loan spreads.

This study provides the first international empirical evidence on the impact of abnormal-temperature-related climate risk on bank loan pricing. Our results suggest that banks perceive abnormal-temperature-related climate risk as a significant factor in firms' overall credit risk. Importantly, borrowers' climate risk disclosures can mitigate banks' concerns about adverse selection. Furthermore, our findings underscore the potential benefits of country-level climate risk disclosure policies in reducing corporate financing costs. With the rising demands for climate risk disclosures, our findings carry significant policy implications for countries aiming to promote either voluntary or mandatory climate risk disclosures.

Our study is subject to some limitations. Although a few countries, such as New Zealand and the United States, have announced their mandatory climate-related risk disclosure requirements in 2022, the compliance date will begin in fiscal year 2023 or later. Many other countries are still actively working to formulate climate risk disclosure rules. Therefore, at present, mandatory climate risk disclosures are not yet available, and voluntary climate risk disclosures are also very limited around the world. To investigate the moderating effect of climate risk disclosures, we use Sautner et al. (2023a)'s climate risk disclosure measure constructed from the transcripts of conference calls conducted in English. Thus, firms conducting conference calls in other languages are not included in our sample. All these data availability issues result in under-representation of non-U.S. firms in our sample, which may limit the generalizability of our results to non-U.S. firms that are not included for these analyses. Nevertheless, our findings provide useful insights into the usefulness of limited voluntary climate-risk disclosures in bank loan contracting with high-climate-risk borrowers. Future research can investigate whether mandatory climate-risk disclosures facilitate debt contracting when such data become available after the phase implementation of mandatory climate risk disclosures in New Zealand, the United States, and some other countries.

Appendix to the Chapter 3: Variable Definitions and Data Sources

Variable	Description	Data source
<u>Loan Characteristics</u>		
LnSpread	The natural logarithm of the loan spread (all-in-drawn spread).	Dealscan
LnTotalCovenant	The natural logarithm of the number of total covenants (i.e., the sum of financial covenants and general covenants).	Dealscan
Collateral	An indicator variable that equals 1 if a loan is secured with collateral, and 0 otherwise.	Dealscan
LoanSize	The natural logarithm of loan facility amount.	Dealscan
LnMaturity	The natural logarithm of loan maturity in months.	Dealscan
PerformancePricing	An indicator variable that equals 1 if a loan uses performance pricing, and 0 otherwise.	Dealscan
LoanPurpose	Indicator variables for loan purposes, including acquisitions, backup line, capital expenditure, corporate purposes, refinancing, working capital, and others.	Dealscan
LoanType	Indicator variables for loan types, including term loan, revolver greater than one year, revolver less than 1 year, and 364-day facility.	Dealscan
<u>Climate Risk Variables</u>		
ClimateRisk	An indicator variable that equals 1 if the annual average absolute value of the return sensitivity to temperature anomaly of a firm is in the highest quintile in its home country, and 0 otherwise.	Self-constructed
ClimateRiskDisclosure	The product of 100000 times "$CCExposure^{Phy}$", which is publicly available from Sautner et al. (2023). "$CCRisk^{Phy}$" measures the percentage of physical shocks bigrams related to climate change (e.g., global warming, snow ice, etc.) appearing in the transcripts of analyst conference calls.	Sautner et al. (2023)
<u>Borrower Characteristics</u>		
FirmSize	The natural logarithm of a borrower's total assets.	Compustat
Profitability	Earnings before interest, taxes, depreciation and amortization (EBITDA)/total assets.	Compustat
Leverage	(Long-term debt + debt in current liabilities)/total assets.	Compustat
Tangibility	Net property, plant and equipment over total assets.	Compustat
MB	Market-to-book ratio of the borrower, measured as market value of equity scaled by book value of equity.	Compustat
CashFlowVolatility	The standard deviation of quarterly cash flows from operations over the four fiscal years prior to the loan initiation year, scaled by the sum of long-term debt and debt in current liabilities. A minimum of 8 observations is required for the calculation.	Compustat

Z-score	Modified Altman's (1968) Z-score in year *t*-1. The Z-score is computed as (1.2 × working capital + 1.4 × retained earnings + 3.3 × EBIT + 0.999 × sales)/total assets, following Graham, Li, and Qiu (2008).	Compustat
Rating	Firms' credit ratings from S&P, Moody's, and Fitch. When S&P ratings are unavailable, Moody's ratings are used. For firms without S&P or Moody's ratings, the Fitch ratings are used. All ratings are converted to conventional linear numeric scores. For example,1 refers to a AAA rating,2 refers to AA+, ..., and 22 refers to D. This variable is set to 23 for firms without a rating from any of these three agencies.	Bloomberg
CFO	Cash flows from operations (OANCF)/total assets	Compustat
ROA	Pre-tax income (PI)/total assets	Compustat
<u>Bank characteristics</u>		
LeadBankExperience	An indicator variable that equals 1 if the sum of each lead bank's climate risk experience for a loan facility is above the sample median, and 0 otherwise.	Dealscan
<u>Macro factors</u>		
GDPGrowth	Annual GDP growth rate.	WDI
PostYear2010	An indicator variable that equals 1 if a loan facility to a U.S. firm starts after the 2010 SEC guidance on climate risk disclosures, and 0 otherwise.	Dealscan
MandatoryESG	An indicator variable that equals 1 if a loan facility starts after the borrower's home country introduced mandatory ESG disclosure, and 0 otherwise.	Dealscan and Krueger et al. (2023)

Chapter 4: Are climate risk disclosures in earnings conference calls relevant to analysts?

4.1. Introduction

Climate change has brought severe challenges to our society and led to unprecedented risks to the aggregate economy and financial system (Litterman et al., 2020). Risk related to climate change (i.e., climate risk) includes the policy risk and technological risk in the transition to a low-carbon economy (also called transition risk) and physical risk related to sea-level rise and extreme weather, which can cause direct damage to physical assets and indirect damage to supply chain or distribution chain. Due to the growing concerns among investors, academia, and regulators about the economic implications of climate risk, there is an emerging literature examining the effects of climate change on firm performance and valuation. Recent studies find that firms with higher climate risk have lower return on assets and higher earnings volatility (Huang et al., 2018), and they tend to engage in earnings management (Ding et al., 2021).

Collecting and analyzing climate-related information is costly and requires vast resources (Hjort, 2016). The U.S. federal securities laws require public firms to submit annual reports on Form 10-K. Although in 2010, the U.S. Securities and Exchange Commission (SEC) provided interpretive guidance on disclosures of climate change risks and opportunities on Form 10-K, only half of S&P 500 firms disclosed climate risk in their 10-K forms and the disclosing firms typically provide only a few lines of boilerplate (Palmiter, 2015; Matsumura et al., 2022). Due to the decline in the quantity and quality of climate risk disclosures in 10-K filings over the years, the SEC mandate has been criticized as a failure (Palmiter, 2015). The SEC has recently launched a comprehensive review of current climate-related disclosure practices in the U.S. and on March 21, 2022, it revealed its proposal to require public companies disclose extensive climate-related risk in their SEC filings.[23] U.S. public firms typically hold conference calls with analysts, investors, and the media following their earnings release each fiscal quarter. An increasing number of public firms discuss the climate risks that they face and their responses to climate issues during conference calls in more detail. Given the increasing demand for credible corporate climate risk disclosures, it is crucial to investigate the relevance of the voluntary climate risk disclosures during conference calls. Security analysts are important information intermediaries in the equity markets and are the key participants in the conference calls. They are specialized in gathering, processing, and producing information (e.g., Francis et al., 2002; Chen et al., 2010; Mayew et al., 2013; Coyne and Stice, 2018; Chen et al., 2022). As key participants in conference calls, they can take the opportunity to pose climate-related questions to managers. It is intriguing to understand whether the voluntary climate risk disclosures reduce information uncertainty and what factors potentially affect the usefulness of these disclosures to analysts. However, there is little evidence whether the managers' discussion of climate risk in conference calls is useful to analysts, so this paper attempts to provide large-sample, systematic evidence on these important but unexplored issues.

Specifically, we first examine whether the climate risk disclosures in conference calls help analysts make more accurate earnings forecasts and reduce forecast dispersion. If climate risk disclosures at conference calls are cheap talks (Kravet and Muslu, 2013; Bao and Datta, 2014; Bingler et al., 2022), such disclosures will have no impact on analyst forecast accuracy. However, recent studies (e.g., Sautner et al., 2023a) find that climate-related conversations during conference calls are less susceptible to "greenwashing" by management, so such information is likely useful

[23] https://www.sec.gov/news/press-release/2022-46. Accessed May 3, 2022.

to analysts. On the one hand, if climate risk disclosures at conference calls reveal previously unknow risk factors and increases the uncertainty of firms' future performance, we predict that climate risk disclosures are associated with higher analyst forecast errors and dispersion. On the other hand, if the climate risk discussions at conference calls resolve known risk factors and reduces information asymmetry between firms and analysts, we predict that climate risk disclosures will reduce analyst forecast errors and dispersion. So, it is an open question whether climate risk disclosures in conference calls affect analyst forecast properties.

To examine this research question, we use climate risk disclosure measures constructed by Sautner et al. (2023a). Sautner et al. (2023a) construct multiple climate risk disclosure measures using the percentage of climate change bigrams appearing in the transcripts of earnings calls, among which three measures, $CCExposure^{Phy}$, $CCExposure^{Reg}$, and $CCExposure^{Opp}$, capture the physical shocks, regulation shocks, and opportunities related to climate risk, and *CCExposure* is a comprehensive climate risk disclosure measure covering all these three dimensions. We first use these four measures to test the effects of climate risk disclosures on analyst forecast errors and dispersion. Using a sample of U.S. public firms followed by at least three analysts from 2002 to 2019, we find that $CCExposure^{Phy}$ is negatively associated with analyst forecast errors and dispersion, but only the effect on analyst forecast errors is statistically significant. *CCExposure*, $CCExposure^{Reg}$, and $CCExposure^{Opp}$ have no significant effect on analyst forecast errors or dispersion. These results suggest that firms' physical climate risk disclosures help analysts to make more accurate earnings forecasts.

Focusing on physical climate risk disclosures ($CCExposure^{Phy}$), we conduct a series of subsample analyses to further analyze under what conditions climate risk disclosures affect analyst forecasts. First, we examine whether the effect of physical climate risk disclosures on analyst forecast accuracy is stronger after the SEC provided explicit guidance on how to disclose material climate risk and opportunities in 10-K filings in 2010. The SEC climate risk disclosure requirements are not mandatory and it is managers' judgment call whether the firm faces material climate risk. Nevertheless, it is reasonable to expect that after the 2010 SEC guidance, there are more meaningful dialogs on climate risk issues in the conference calls and firms are more likely to take the opportunity to explain the climate risk that they face and their adaptation to climate change risk, so we predict that the effect of physical climate risk disclosures on analyst forecast accuracy is more pronounced after 2010. Consistent with our prediction, we find $CCExposure^{Phy}$ has significant, negative effects on analyst forecast errors and dispersion in the subsample period of 2011 to 2019, while it has no significant effect on analyst forecast errors or dispersion in the subsample period of 2002 to 2010.

Second, some industries, such as construction, communication, energy, healthcare, agriculture, business services, and transportation, are more vulnerable to physical damages caused by climate change than others (Challinor et al., 2014; Fleming et al., 2006; Hsiang, 2010; McCarthy et al., 2001; SASB, 2016), and the risk perceptions of outside stakeholders in these industries will be higher (Kim et al., 2023). Being closely watched by outside stakeholders, we expect that firms in these high-sensitive industries are likely to disclose more useful climate risk information. Our results indicate that physical risk disclosures in conference calls are significantly associated with smaller analyst forecast errors and dispersion in the high-sensitivity industries only.

Third, we examine whether the physical climate risk information disclosed by firms located in regions that are more seriously impacted by extreme weather events is more useful in improving analyst forecast accuracy. Firms located in regions that are more seriously impacted by extreme weather events are subject to high climate risk, so there could be more climate risk-related conversations in conference calls held by these firms, and analysts could extract and use useful information in their analyses. We use the Climate Extremes Index and Billion-Dollar Weather and Climate Disasters data from the U.S. National Oceanic and Atmospheric Administration to categorize our sample into firms in the region-years with high versus low climate extremes index and high versus low disaster costs, respectively. Consistent with our prediction, we find that physical climate risk disclosures have significant impacts on reducing analyst forecast errors and dispersion for firms in region-years that are affected more by extreme weather or disasters.

Fourth, not all Americans believe climate change is happening, and there is significant variation in climate change beliefs across the U.S. (Addoum et al., 2023). If managers do not believe climate change imposes risks to firms and society, their climate risk discussions at conference calls would be superficial and even misleading. So, we expect the physical climate risk information disclosed by firms located in regions where people have stronger beliefs in climate change to be more useful in improving analyst forecast accuracy. Using the percentage of adults who think global warming is happening from the Yale Program on Climate Change Communication, we categorize the U.S. states into states with high versus low beliefs. Our results are consistent with our prediction.

We conduct several robustness tests. Specifically, we construct a propensity score matched (PSM) sample of firms disclosing climate physical shocks and non-disclosing firms, expand our sample by including firms followed by two analysts, and extend our sample period to the COVID-19 period. We also add physical risk disclosures in 10-Ks as an additional control and conduct the tests for a reduced sample not disclosing physical risk in their 10-Ks. Our baseline results are robust to these sensitivity tests.

This study makes several contributions. First, it adds to a growing literature on the effects of climate risk disclosures. Matsumura et al. (2014) and Griffin et al. (2017) examine the voluntary carbon or gas emission disclosures from the Carbon Disclosure Project. Both studies find that the equity market penalizes firms for carbon or gas emissions, however, Matsumura et al. (2014) find that the market penalizes non-disclosing firms more while Griffin et al. (2017) document that the valuation discount does not differ between disclosing and non-disclosing firms. Focusing on climate risk disclosures in 10-K filings, Bao and Datta (2014) find that about two-thirds of climate risk types do not affect the risk perceptions of investors, while recent studies report that disclosing firms tend to engage more in pro-environmental activities and less in anti-environmental activities (Kim et al., 2023) and have lower cost of equity than non-disclosing firms (Matsumura et al., 2022). There is also some empirical evidence that certain types of climate risk disclosed in earnings conference call transcripts are priced by investors (Li et al., 2021; Sautner et al., 2023a, 2023b). The above studies have focused on equity market valuation of firms disclosing climate risk information, while our paper examines the informativeness of climate risk disclosures in conference calls to securities analysts.

Second, it contributes to the emerging literature examining the effect of climate change on analyst forecasts. Han et al. (2020) find that climate disasters distract analysts and lead to higher earnings forecast errors. Cuculiza et al. (2021) report that analysts in high-temperature-sensitive states are more likely to issue less optimistic and more accurate forecasts following abnormally warm climate, while Pankratz et al. (2023) document that analysts do not fully anticipate the financial effect of heat as a first-order physical climate risk. Different from these studies, we focus on the effect of voluntary climate risk disclosures in earnings conference calls, rather than the climate change itself, on analyst forecasts. Our study provides initial evidence that voluntary physical risk disclosures in conference calls help analysts make more accurate earnings forecasts. Our subsample analyses also shed light on the conditions under which the physical risk disclosures are more useful to analysts.

Third, our findings have important practical implications for managers, investors, and regulators. The positive effect of voluntary climate risk disclosures documented in our study can encourage managers to make credible, voluntary disclosures of climate risk and take effective actions to cope with climate change. Our findings can also serve as a reminder to investors to gather corporate climate risk information from various credible channels and incorporate such information into their decision making. In addition, many countries such as the U.S., Canada, and European countries are proposing climate risk or sustainability disclosure regulations. Our findings highlight the importance of engaging managers in providing relevant climate risk disclosures and lend support to the on-going regulatory reforms.

The paper proceeds as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 describes our research design, data sources and sample. Section 4 reports the baseline regression results and subsample analyses. Section 5 presents additional tests, and Section 6 concludes.

4.2. Literature review and hypothesis development

Given the important implications of climate change for the economy and financial markets, there is an emerging literature exploring whether climate risk is priced in financial markets. These studies generally use macro climate risk measures, such as sea level rise risk (Painter, 2020; Jiang et al., 2020) or the drought trend resulting from global warming (Hong et al., 2019), assuming that firms have the same exposure to climate risk. However, firms even within the same industry may have different levels of climate risk due to different firm-level managerial skills, innovations, financial constraints (Sautner et al., 2023a), and thus different levels of operational resilience to climate change through improving infrastructure and production techniques, relocating activities, and increasing insurance coverage (Berkhout et al., 2006; Hoffmann et al., 2009).

Recent studies seek to extract climate risk information from 10-K filings or the transcripts of conference calls. Bao and Datta (2014) show that two-thirds of general risk types disclosed in 10-K forms do not affect the risk perceptions of investors, while Matsumura et al. (2022) find that firms disclosing climate risk in 10-K forms have lower cost of equity than non-disclosers. Using textual analysis of climate risk information contained in conference call transcripts, Li et al. (2021) report that firms facing higher transition risk have lower firm valuation. Sautner et al. (2023a) document that firm exposure to climate-related regulatory shocks negatively affects firm valuations in recent years. Sautner et al. (2023b) find that when extracted from realized stock returns, the unconditional risk premium for firm-level climate change exposure is insignificant but forward-looking expected return proxies deliver an unconditionally positive risk premium. These findings suggest that not all types of climate risk disclosures are relevant to investors.

One of the important tasks of analysts is to make earnings forecasts. Following the literature, we use analyst forecast accuracy and dispersion to capture the relevance of disclosures to analysts (e.g., Lehavey et al., 2011; Dhaliwal et al., 2012; Demmer et al., 2019; Muslu et al., 2019). Climate risk disclosures in conference calls may affect analyst forecasts in three different ways.

First, the climate risk disclosures in conference calls are voluntary and discretionary. Managers may disclose climate risk in order to cater to the investor's attention (Sautner et al., 2023b) or environmental shareholder activism (Flammer et al., 2019). In this case, climate risk disclosures, regardless in 10-K filings or in conference calls, are boilerplate or cheap talk and thus not useful (Kravet and Muslu, 2013; Bao and Datta, 2014; Bingler et al., 2022). Accordingly, we will not observe a significant effect of climate risk disclosure on analyst forecast errors or dispersion. This is our null hypothesis.

Second, recent studies find that disclosure readability (Bonsall and Miller, 2017) and specificity (Hope et al., 2016) affect the usefulness of mandatary disclosure of general risk factors in firms' 10-K forms. Unlike risk disclosures in 10-K forms, which are criticized as generic (Hope et al., 2016), there are real time conversations between analysts and management during conference calls. Analysts can ask probing questions directly related to climate risk to get specific information in plain languages. Climate-related conversations during conference calls are much less susceptible to "greenwashing" by management (Sautner et al., 2023a). To the extent that risk disclosures reveal previously unknown risk factors and adversely affect analysts' judgments on firms' future performance, we expect that climate risk disclosures are associated with higher analyst forecast errors and dispersion.

Third, if detailed climate-related discussions during conference calls resolve known risk factors, reveal firms' adaptation to the changing environmental conditions, and demonstrate firms' operational resilience to climate change and natural disasters, such disclosures can reduce the information asymmetry between the analysts and the firm, and then decreases the range of analysts' predictions. Therefore, climate risk disclosure will reduce analyst forecast errors or dispersion.

Based on the above discussion, we develop the following competing hypotheses stated in the alternative form:

H_{1A}: Climate risk disclosures in conference calls are positively associated with analyst forecast errors and dispersion. (Revealing Unknown Risk Factor Hypothesis)

H_{1B}: Climate risk disclosures in conference calls are negatively associated with analyst forecast errors and dispersion. (Resolving Known Risk Factor Hypothesis).

4.3. Research Design

4.3.1. Baseline regression model

To investigate the impact of climate risk disclosures on analyst forecast properties, we estimate the following regression model:

$$AF = \phi(Climate\ Risk\ Disclosure, X, \text{IndustryEffects}, \text{YearEffects}) \quad (5)$$

where, the dependent variable, analyst forecast properties (*AF*), refers to analyst forecast errors (*FERROR*) and dispersion (*DISPERSION*), respectively. Following the literature (e.g., Dhaliwal et al., 2012), we use analyst forecast error as an inverse measure of analyst forecast accuracy. *FERROR* is the average of absolute forecast error scaled by the stock price at the beginning of the year, calculated as follows:

$$FERROR_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \left| FEPS_{i,t,j} - AEPS_{i,t} \right| / Begin\_price_{i,t} \quad (6)$$

where, $FEPS_{i,t,j}$ is the EPS forecast for firm *i* in year *t* made by analyst *j*. $AEPS_{i,t}$ is the actual EPS of firm *i* in year *t*. $N_{i,t}$ is the number of analysts following firm *i* in year *t*. $Begin\_price_{i,t}$ is the beginning share price of firm *i* on the first trading day in year *t*.

Forecast dispersion is the standard deviation of individual analysts' earnings forecast scaled by the stock price at the begging of the year. It is calculated as follows:

$$DISPERSION_{i,t} = \frac{\sqrt{\frac{1}{N_{i,t}}\sum_{j=1}^{N_{i,t}}(FEPS_{i,t,j} \quad -Mean\ FEPS_{i,t})^2}}{Begin\_price_{i,t}} \tag{7}$$

In Eq. (3), *Mean* $FEPS_{i,t}$ is the mean value of the analyst earnings forecasts made for firm *i* in year *t*.

We use four climate risk measures constructed by Sautner et al. (2023a) to capture climate risk disclosures, *CCExposure*, $CCExposure^{Phy}$, $CCExposure^{Reg}$, and $CCExposure^{Opp}$. *CCExposure* is the relative frequency with which bigrams related to climate change occur in the transcripts of annual earnings conference calls.[24] *CCExposure* further breaks down into three sub-exposures based on the topics: physical shocks ($CCExposure^{Phy}$) (e.g., global warm, snow ice, sea level rises), regulatory shocks ($CCExposure^{Reg}$) (e.g., carbon tax, carbon reduction, dioxide emission), and opportunities related to climate change ($CCExposure^{Opp}$) (e.g., new energy, wind energy, renewable resource). We multiply the relative frequency by 100 to express these four variables in percentage.

X represents a vector of control variables that may affect analyst forecast accuracy. Following Dhaliwal et al. (2012), Liu and Natarajan (2012), and Muslu et al. (2019), we control for forecast horizon (*FHORIZON*), the number of analysts following a firm (*ANANO*), firm size (*SIZE*), an indicator for the loss status (*LOSS*), earnings volatility (*ROAVOL*), leverage (*LEV*), an indicator for the R&D status (*RD*), and book-to-market ratio (*BM*). We also control for year and industry

[24] One could view the climate risk information revealed during conference calls as an indicator of climate risk. However, according to Sautner et al. (2023a), these metrics primarily reflect "the attention that financial analysts and management allocate to climate change topics at a specific moment in time", which suggests that they do not directly measure risk. Furthermore, from an accounting standpoint, any information divulged by companies through 10-K filings or conference calls is a component of their disclosures. While these disclosures could potentially influence market participants' risk assessments, they might not necessarily enhance their risk perception; instead, they could help reduce information asymmetry.

(Fama-French 48 industries) fixed effects.[25] The standard errors of the estimated coefficients are adjusted for firm-level clustering. The appendix provides detailed definitions and data sources for all these variables.

4.3.2. Data and sample

We extract analyst forecasts from I/B/E/S detailed file. We keep only the most recent forecast of each analyst each year (Bradley et al., 2017; Francis et al., 2019). Firms with stock price less than one dollar are excluded from our sample (Francis et al., 2019; Cuculiza et al., 2021). We drop firm-year with less than three analysts (Barniv et al., 2005). We obtain the annual climate risk disclosure data from Sautner et al. (2022a), which is available from 2002 to 2020.[26] The accounting data and stock prices are from Compustat and CRSP, respectively. After merging data from these sources and dropping observations with missing values, our sample contains 31,006 firm-year observations from 2002 to 2019. Our sample period ends at 2019 to eliminate the potential effect of COVID-19 on the economy and analyst forecasts. We winsorize all firm-level continuous variables at the 1st and the 99th percentiles.[27]

Table 4.1 presents the descriptive statistics of main variables. The mean values of *FERROR* and *DISPERSION* are 0.0154 and 0.0129, respectively. The mean values of climate risk disclosure measures are small, which is not surprising as firms often cover many other topics in earnings conference calls and not all firms make climate risk disclosures. The descriptive statistics of $CCExposure^{Phy}$, $CCExposure^{Reg}$, and $CCExposure^{Opp}$ indicate that less than 25% of our sample firms disclose physical or regulatory risks related to climate change, but more than 50% of firms

[25]. Our main findings remain unaffected even after considering firm fixed effects.
[26]Available at https://osf.io/fd6jq/.
[27] We do not winsorize climate risk disclosures because by construction, these measures have small values and only a small portion of the sample has non-zero climate disclosures.

discuss opportunities related to climate change.[28] The statistics of firm characteristics indicate that our sample covers both small and large firms (the median firm size is $1549 million). About 22.7% our sample firms report a loss, and on average, our sample firms are followed by 12 analysts. They have low earnings volatility and low leverage ratio, more than half of the sample firms invest in R&D, and their market value is higher than book value.

[Insert Table 4.1 Here]

4.4. Empirical Results

4.4.1. Baseline regression results

Table 4.2 reports the baseline regression results of testing the effects of climate risk disclosures on analyst forecast errors and dispersion, using four measures of climate risk disclosures, *CCExposure*, $CCExposure^{Phy}$, $CCExposure^{Reg}$, and $CCExposure^{Opp}$. We find that the coefficient of climate physical risk disclosures ($CCExposure^{Phy}$) is significantly negative in column (3) where the dependent variable is *FERROR*, and negative but insignificant in column (4) where the dependent variable is *DISPERSION*. The result on analyst forecast errors is consistent with H_{1b}, suggesting that disclosures of physical risk related to climate change in conference calls reduce information asymmetry and help analysts make more accurate earnings forecasts. As shown in columns (1), (2), (5) and (6) of Table 4.2, the aggregate climate risk disclosures (*CCExposure*) and disclosures on regulatory shocks ($CCExposure^{Reg}$) or opportunities ($CCExposure^{Opp}$) related to climate change have no significant effect on analyst forecast errors or dispersion. This is probably because climate-change related regulatory shocks or opportunities have no immediate effect on

[28] Untabulated data shows that the percentage of our sample with non-zero $CCExposure^{Phy}$, $CCExposure^{Reg}$, and $CCExposure^{Opp}$ is 6.75%, 13.24%, and 53.27%, respectively.

firm performance or analysts are aware of the climate-change related regulations so such disclosures do not provide incremental value to analysts in their information production.[29] So, for the subsample analyses, we focus on the effect of $CCExposure^{Phy}$ on analyst forecast errors and dispersion.

The results on control variables indicate that analysts make more accurate analyst forecasts (smaller forecast errors and dispersion) for large firms, while the forecast errors and dispersion are larger for unprofitable firms and firms with higher earnings volatility, leverage, and BM ratios.

[Insert Table 4.2 Here]

4.4.2. Subsample analyses

In this section, we conduct subsample analyses to examine under what conditions the disclosures of physical shocks related to climate change have a stronger effect on analyst forecast accuracy.

4.4.2.1. Subsample analyses: before and after the 2010 SEC guidance

In January 2010, the SEC provided guidance on disclosures of climate change risks and opportunities in their 10-K filings. The overall climate risk information disclosed by firms is more available after 2010 because not disclosing climate risk information may result in litigations (Kölbel et al., 2021). Therefore, analysts are more likely to ask questions about climate risk and firms are more likely to take the opportunity in conference calls to explain the climate risk that they face and more importantly, their adaptation to climate change risk. This regulatory effort

[29] The positive coefficients of $CCExposure^{Opp}$ on analyst forecast errors and dispersion (columns (5) and (6)), though not significant, are consistent with the theoretical model and empirical results in Kölbel et al. (2021). They find that transition risk disclosure reveals new risks and then increase the CDS spreads, while disclosing physical risk deceases CDS spreads by reducing uncertainty.

increases the awareness of the importance of both providing and using climate risk information, so we expect the effect of physical climate risk disclosures on analyst forecast accuracy to be stronger in the post-2010 period.

We estimate Eq. (1) for the subsample from 2002 to 2010 and the subsample from 2011 to 2019, respectively. As shown in Table 4.3, the estimated coefficients of $CCExposure^{Phy}$ are not significant in the period 2002-2010 (columns (1) and (3)), but significantly negative in the period 2011-2019 (columns (2) and (4)), suggesting physical climate risk disclosures only significantly reduce analyst forecast errors and dispersion after the 2010 SEC guidance.[30]

[Insert Table 4.3 Here]

4.4.2.2. Subsample analyses: industry sensitivity to climate risk

The risk exposures to climate change are not homogenous across industries. Industries with significant long-lived physical assets (e.g., construction, communication, energy, and healthcare) and those dependent on extended supply chains and infrastructures (e.g., agriculture, business services, and transportation) are more vulnerable to physical risk related to climate change (Challinor et al., 2014; Fleming et al., 2006; Hsiang, 2010; McCarthy et al., 2001; SASB, 2016). The larger climate change exposures of these industries will increase the risk perceptions of outside stakeholders (Kim et al., 2023). Therefore, firms in weather-sensitive industries may be more willing to disclose useful climate risk information to cater to outside stakeholders' need for informative risk disclosures. Following Kim et al. (2023), we assign firms in agriculture,

[30] Unreported results reveal that, on average, the disclosure of physical climate risks witnessed a significant surge from 2001 to 2007. However, we did not observe a substantial increase in physical climate risk disclosure after 2010. These results suggest that the effects of disclosure on analysts' forecast accuracy or dispersion, which became significant only after 2010, are more likely attributed to the enhanced reliability of disclosure rather than its mere quantity.

automobile and trucks, business services, communication, construction, energy, health care, pharmaceutical products, and transportation to the high-sensitivity group, and firms in other industries to the low-sensitivity group.

Table 4.4 reports the results for the high versus low-sensitivity groups. We find that the coefficients of $CCExposure^{Phy}$ are negative in all columns, but significant in high-sensitivity group only (columns (2) and (4)). These results indicate that physical risk disclosures help analysts make more accurate earnings forecasts with less dispersion for firms in industries that are more subject to physical damages caused by climate change.

[Insert Table 4.4 Here]

4.4.2.3. Subsample analyses: extreme weather events

The literature documents that investor's attention to climate risk increases after extreme weather (Choi et al., 2020; Giglio et al., 2021). Analysts are more likely to inquire climate risk information and pose questions to firms located in regions that are more affected by extreme weather. Upon the greater pressure from investors or analysts, firms subject to higher climate risk are more likely to provide more specific, informative climate risk disclosures when meeting with analysts in conference calls. Such information will help analysts better assess the effect of climate risk on firm performance. Thus, we predict that the effect of climate risk disclosures on analyst forecast accuracy is stronger for firms located in regions that are more seriously impacted by extreme weather events.

We extract Climate Extremes Index (CEI) and Billion-Dollar Weather and Climate Disasters (BDWCD) data from the U.S. National Oceanic and Atmospheric Administration (NOAA). CEI measures the average percentage of the occurrence of several extreme weather indicators, including extreme high temperatures, extreme low temperatures, severe drought, severe moisture, extreme precipitation, landfalling tropical storm, and hurricane wind velocities. BDWCD only directly estimates the cost of weather and climate disasters, such as drought, floods, freezing temperatures, severe storms, tropical cyclones, wildfires, and winter storms. Both databases group the U.S. states into the same nine regions.[31] For the CEI and BDWCD data, we categorize the region-year observations into region-years with high versus low CEI (or disaster costs) based on median CEI (or disaster costs), respectively. We merge the CEI or BDWCD data with firm-level information based on where a firm is headquartered. The historical 10K headquarter information is from Augmented 10-X Header Data provided by the University of Notre Dame. We conduct analyses for the paired subsamples with high versus low CEI or disaster costs.

Panel A of Table 4.5 reports the results for subsamples with high versus low CEI and Panel B reports the results for subsamples with high versus low disaster costs. The coefficients of $CCExposure^{Phy}$ in both panels are significantly negative for firms in the region-years with high CEI or high disaster costs only (columns (2) and (4)), suggesting the disclosures of physical shocks related to climate change are more informative to analysts for predicting a firm's EPS when extreme weather events are more likely to occur in the region where the firm is located. Pankratz et al. (2019) and Addoum et al. (2019) find that analysts do not sufficiently take the effect of heat shocks into account, while our results indicate that climate risk disclosure is important for analysts following firms located in regions that are affected more by the climate change.

[Insert Table 4.5 Here]

[31] Northeast: CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT; Upper Midwest: IA, MI, MN, WI; Ohio Valley, IL, IN, KY, MO, OH, TN, WV; Southeast, AL, FL, GA, NC, SC, VA; Northern Rockies and Plains: MT, NE, ND, SD, WY; South: AR, KS, LA, MS, OK, TX; Southwest: AZ, CO, NM, UT; Northwest: ID, OR, WA; West: CA, NV.

4.4.2.4. Subsample analyses: beliefs on global warming

There is significant variation in climate change beliefs across the U.S. (Addoum et al., 2023). If people do not believe climate change is happening and thus are unaware of climate risk, firms' self-assessment of climate risk that they face will be inaccurate and their strategies of dealing with climate risk will be less effective. The climate risk information that they provide in conference calls will be less useful. Therefore, we expect that the climate risk information disclosed by firms headquartered in areas where more people believe in climate change are more informative, so the effect of climate risk disclosures on analyst forecast accuracy is stronger for firms located in regions where people have stronger beliefs in climate change.

We extract people's beliefs on global warming from Yale Program on Climate Change Communication (YPCCC), which provides the percentage of adults who think global warming is happening at the state level from 2008. We first calculate the state-level beliefs in global warming by averaging the percentage of adults in that state who believe global warming across the years with available belief data, and then categorize the states into states with high versus low beliefs based on median value.[32] We merge the beliefs data with firm-level information based on the location of a firm's headquarters. We estimate Eq. (1) for firms in the high-belief states and firms in the low-belief states, respectively.

Columns (1) and (2) of Table 4.6 report the results when the dependent variable is *FERROR*, and columns (3) and (4) report the results when the dependent variable is *DISPERSION*. We find

[32] We also use an alternative approach, that is, for the YPCCC data, we categorize state-year observations with available beliefs data into state-years with high versus low beliefs based on the median value. After merging the beliefs data with firm-level data, we run regression for the sample from 2008 to 2019 since the beliefs data is available after 2008. The results are generally consistent with those reported in Table 4.5 except that the negative coefficient of $CCExposure^{Phy}$ in column (1) becomes marginally significant.

that in states with stronger beliefs in global warming, *CCExposure*^{Phy} is significantly associated with smaller analyst forecast errors (column (2)) and dispersion (column (4)), while in low-belief states, the coefficients of *CCExposure*^{Phy} are negative but not statistically significant (columns (1) and (3)). This analysis is based on where firms are located not where analysts are located. For firms located in low-belief states, if the analysts are concerned about global warming, they would still utilize the disclosed climate risk information for their analyses. The results imply that firms in low-belief states underestimate the effect of climate change on their performance so the disclosed physical risk information is less accurate and less useful for analysts to make earnings forecasts.

[Insert Table 4.6 Here]

4.5. Robustness tests and additional analysis

4.5.1. PSM sample

To reduce the concern that our results may be driven by the inherent differences between firms disclosing physical shocks related to climate change and non-disclosing firms, we construct a PSM sample. We first generate an indicator variable (*D_CCExposure*^{Phy}) that equals 1 for firms disclosing physical shocks related to climate change, and 0 otherwise. We then compute the propensity score after running a probit regression of the probability of *D_CCExposure*^{Phy} =1 on the firm-level control variables in Eq. (1). We also control for year and industry fixed effects in this stage. Next, for each firm-year observation in the disclosing group, we use the closest propensity score to identify matched firm-year observations in the non-disclosing group, yielding 4052 observations in the PSM sample (2093 from the disclosing group and 1959 from non-disclosing group). Table 4.7 reports the results for the PSM sample. We find that our baseline findings are robust to the PSM sample.

[Insert Table 4.7 Here]

4.5.2. Expanding the sample to firms followed by at least two analysts

Our sample consists of firms followed by at least three analysts. As a sensitivity test, we expand our sample by including firms followed by at least two analysts. As reported in Table 4.8, the effect of $CCExposure^{Phy}$ on reducing analyst forecast errors still holds for this expanded sample.

[Insert Table 4.8 Here]

4.5.3. Adding COVID period

As explained in Section 3.2, we exclude the COVID-19 period to eliminate the confounding effect of COVID-19 on the economy and analyst forecasts. As a robustness test, we extend our sample period to 2020 as the climate risk variables constructed by Sautner et al. (2023a) are available up to 2020. As shown in Table 4.9, the negative coefficient of $CCExposure^{Phy}$ is significant at the 10% level when the dependent variable is *FERROR* and insignificant when the dependent variable is *DISPERSION*, consistent with our baseline results.

[Insert Table 4.9 Here]

4.5.4. Controlling for physical risk disclosures in 10-Ks

Since 2006, U.S. firms are required to include a specific section (Item 1.A) that reveal significant risk factors to their business in their 10-K reports. Some firms, especially after the 2010 SEC guidance on climate risk disclosures in 10-Ks, choose to disclose climate risk information in the Item 1.A of their 10-K reports. To mitigate the concern that our results may be driven by the physical risk disclosures in 10-Ks, as a robustness test, we control for 10-K physical risk disclosure variable (*Physical10K*) constructed by Kölbel et al. (2021). *Physical10K* is the percentage of sentences related to physical risk in the Item 1.A of a firm's 10-K report. Since only a small portion of firms make such disclosures in their 10-Ks, we set *Physical10K* to 0 if *Physical10K* is missing after merging the 10-K risk data with our sample. As shown in Table 4.10, the coefficients of *Physical10K* are negative but insignificant in both columns. After controlling for *Physical10K*, the results on $CCExposure^{Phy}$ are consistent with our baseline results.

[Insert Table 4.10 Here]

We also delete observations with non-zero *Physical10K* and re-estimate Eq. (1) for this subsample of firms not disclosing physical climate risk in their 10-Ks. The results (not tabulated for brevity) remain similar and the negative coefficient of $CCExposure^{Phy}$ is significant at the 10% level when the dependent variable is *FERROR*.

4.6. Conclusion

In this paper, we examine whether firms' voluntary climate risk disclosures in earnings conference calls provide useful information to help analysts make more accurate earnings forecasts with less dispersion. Using the climate risk disclosure variables constructed by Sautner et al. (2022a), we find that physical climate risk disclosures are associated with more accurate analyst earnings forecasts, measured by smaller forecast errors, while regulatory and opportunity shocks related to climate change disclosed in conference calls have no such impact.

We further conduct cross-sectional analyses to shed light on what moderates or strengthens the effects of physical climate risk disclosures on analyst forecast properties. Our analyses reveal the following. First, physical climate risk disclosures are associated with smaller analyst forecast errors and dispersion after, not before, the SEC provided guidance in 2010 on disclosing climate risk and opportunities in 10-Ks. Second, the negative effect of physical risk disclosures on analyst forecast errors and dispersion are significant in firms that are more sensitive to climate change. Third, the effects of physical climate risk disclosures on reducing analyst forecast errors and dispersion are observed for firms located in regions that are more affected by extreme weather events or have higher disaster costs. Fourth, the effects of physical climate risk disclosures on analyst forecast errors and dispersion concentrate in firms located in states where people have stronger beliefs in climate change.

Our results are robust to the PSM sample, the expanded sample including firms followed by at least two analysts, and the sample extending to 2020, the COVID-19 period. Our results also hold after controlling for the physical risk disclosures in 10-Ks and for a reduced sample not disclosing physical risk in their 10-Ks. Taken together, our findings suggest that physical climate risk disclosures in earnings conference calls help analysts make more accurate earnings forecasts.

This study contributes to a growing literature on climate risk disclosures and their effects on analysts' information production. We provide novel evidence that disclosures of physical climate risk are informative to analysts, while other types of climate change disclosures are not useful in improving analyst forecast accuracy. Our findings provide insights to regulators who are proposing standards for climate risk disclosures and have practical implications for managers and capital market participants.

Appendix to the Chapter 4: Variable Definitions and Data Sources

Variable	Description	Data source
Dependent Variable		
FERROR	The average of absolute earnings forecast errors scaled by the stock price at the beginning of the year.	I/B/E/S
DISPERSION	The standard deviation of individual analysts' earnings forecasts scaled by the stock price at the beginning of the year.	I/B/E/S
Climate Risk Disclosure		
CCExposure	Relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls. It equals the number of such bigrams divided by the total number of bigrams in the transcripts. We multiply the relative frequency by 100 to express this variable in percentage.	Sautner et al. (2022a)
$CCExposure^{Phy}$	Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of earnings conference calls. We multiply the relative frequency by 100 to express this variable in percentage.	Sautner et al. (2022a)
$CCExposure^{Reg}$	Relative frequency with which bigrams that capture regulation shocks related to climate change occur in the transcripts of earnings conference calls. We multiply the relative frequency by 100 to express this variable in percentage.	Sautner et al. (2022a)
$CCExposure^{Opp}$	Relative frequency with which bigrams that capture opportunity shocks related to climate change occur in the transcripts of earnings conference calls. We multiply the relative frequency by 100 to express this variable in percentage.	Sautner et al. (2022a)
Firm Characteristics		
ANANO	The natural logarithm of the number of analysts following a firm in a given year.	I/B/E/S
FHORIZON	The median number of days between analyst forecast date and the earnings announcement date among all analysts in a given year.	I/B/E/S
SIZE	The natural logarithm of a firm's total assets.	Compustat
LOSS	An indicator variable that equals 1 if negative earnings are reported in a given year, and 0 otherwise.	Compustat
ROAVOL	The standard deviation of ROA over the past five fiscal years. A minimum of 3 observations is required.	Compustat
RD	An indicator variable that equals 1 if firm reports research and development expense, and 0 otherwise.	Compustat

LEV	(Long-term debt)/total assets	Compustat
BM	Book-to-market ratio of the borrower, measured as book value of equity scaled by market value of equity.	Compustat

Chapter 5: General Conclusion

This dissertation comprises three essays focusing on climate finance and international finance. The first essay pioneers the use of machine learning techniques to predict corporate bond returns worldwide. Notably, it represents the initial investigation into the cross-sectional predictability of corporate bond returns in international markets using machine learning methods. The second essay delves into the impact of abnormal-temperature-related climate risk on bank loan pricing. The third essay examines the influence of climate risk disclosures in earnings conference calls on analyst forecast errors and dispersion. The last two essays contribute to the literature by uncovering the usefulness of voluntary climate-risk disclosures in the financial market. Our findings hold significant implications for both industry and regulators, particularly as an increasing number of countries take steps to formulate climate risk disclosure regulations.

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Figure 2.1: Characteristic Importance in the U.S. Market

This figure presents the overall rankings of 21 bond characteristics 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 monthly 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 the lowest R-squared reduction has a variable importance of 0, while the characteristic with the highest R-squared reduction has a 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.

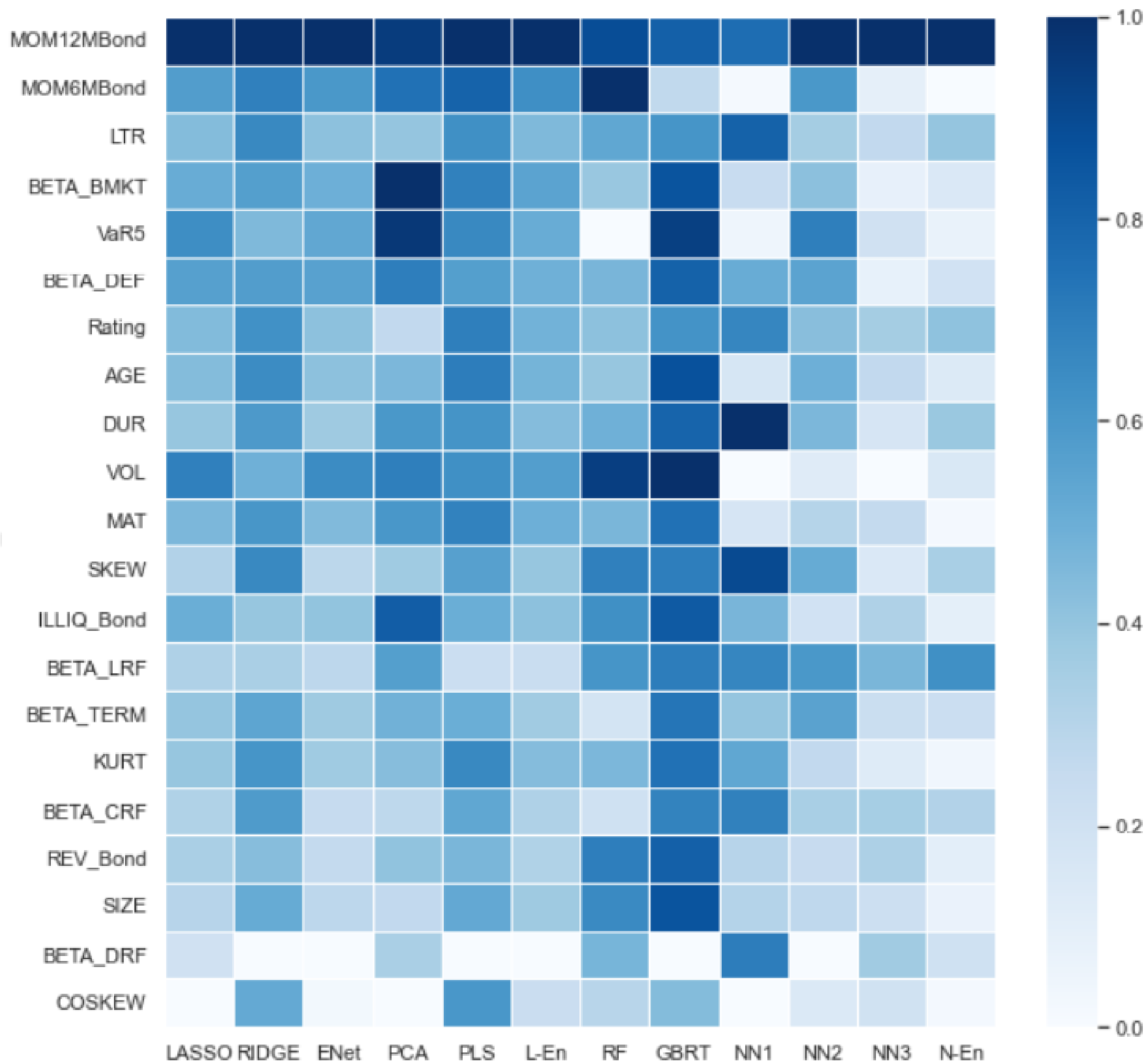

Figure 2.2: Characteristic Importance in the Non-U.S. Developed Market

This figure presents the overall rankings of 21 bond characteristics 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 monthly 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 the lowest R-squared reduction has a variable importance of 0, while the characteristic with the highest R-squared reduction has a 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.

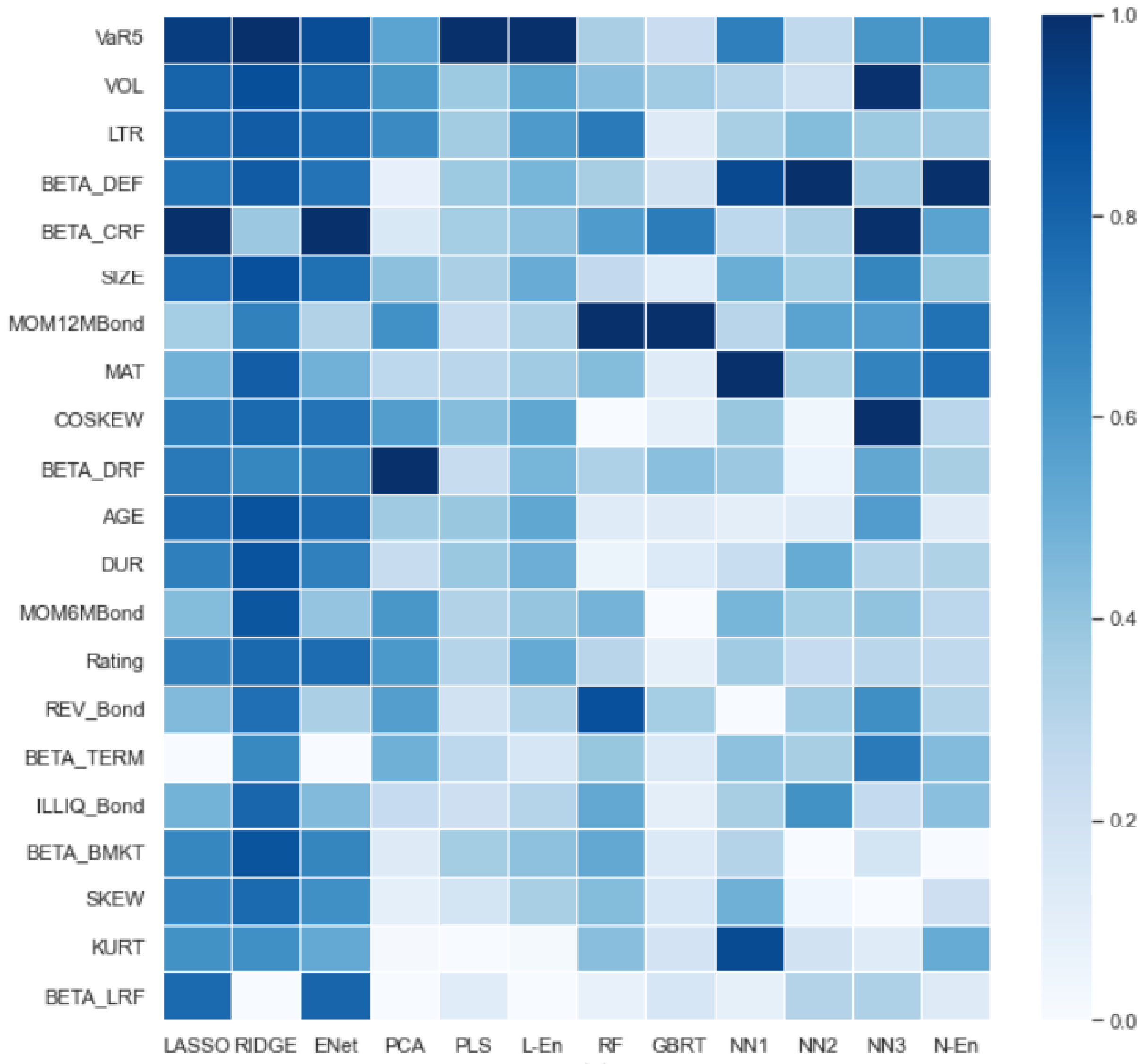

Figure 2.3: Characteristic Importance in the Emerging Market

This figure presents the overall rankings of 21 bond characteristics based on variable importance in each model in the emerging market. To measure variable importance, we first calculate the reduction of time-series average monthly 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 the lowest R-squared reduction has a variable importance of 0, while the characteristic with the highest R-squared reduction has a 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.

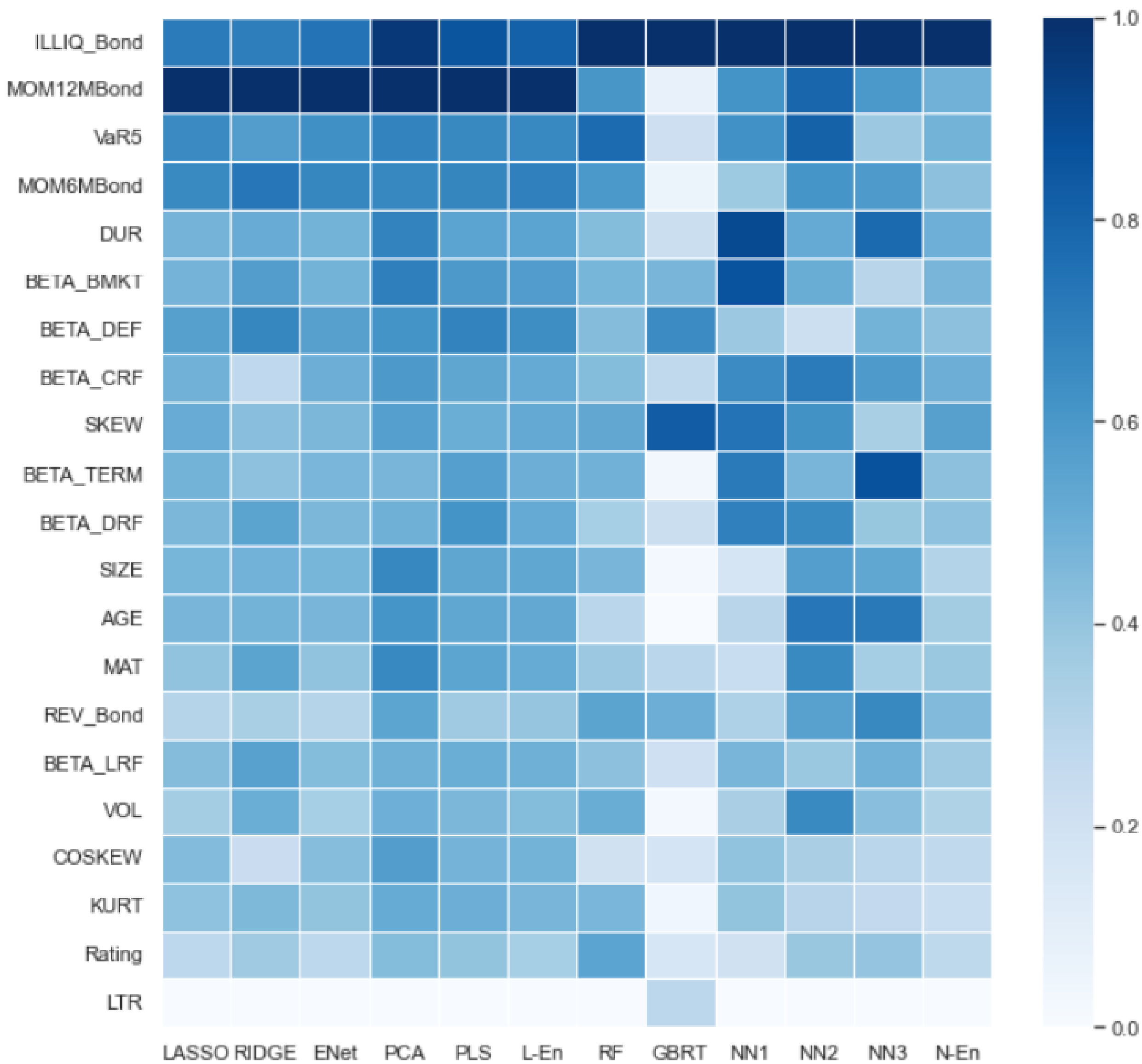

Figure 2.4: Bond Market Integration and Stock Market Integration

This figure presents the correlation between bond market integration and stock markets integration. Bond market integration for each is measured by the relative change of R^2_{OOS} after adding the exposures to U.S. bond factors (including BMkt, DEF, LRF, CRF, and DRF) as new predictors. We average the forecasts of 10 machine learning models to estimate R^2_{OOS}. Stock market integration comes from Akbari et al. (2020), who decompose stock returns into cash-flow revision and risk-pricing revision, and the stock market cross-country integration measures the extent to which a country's risk-pricing revision comoves with the world-level risk-pricing revision.

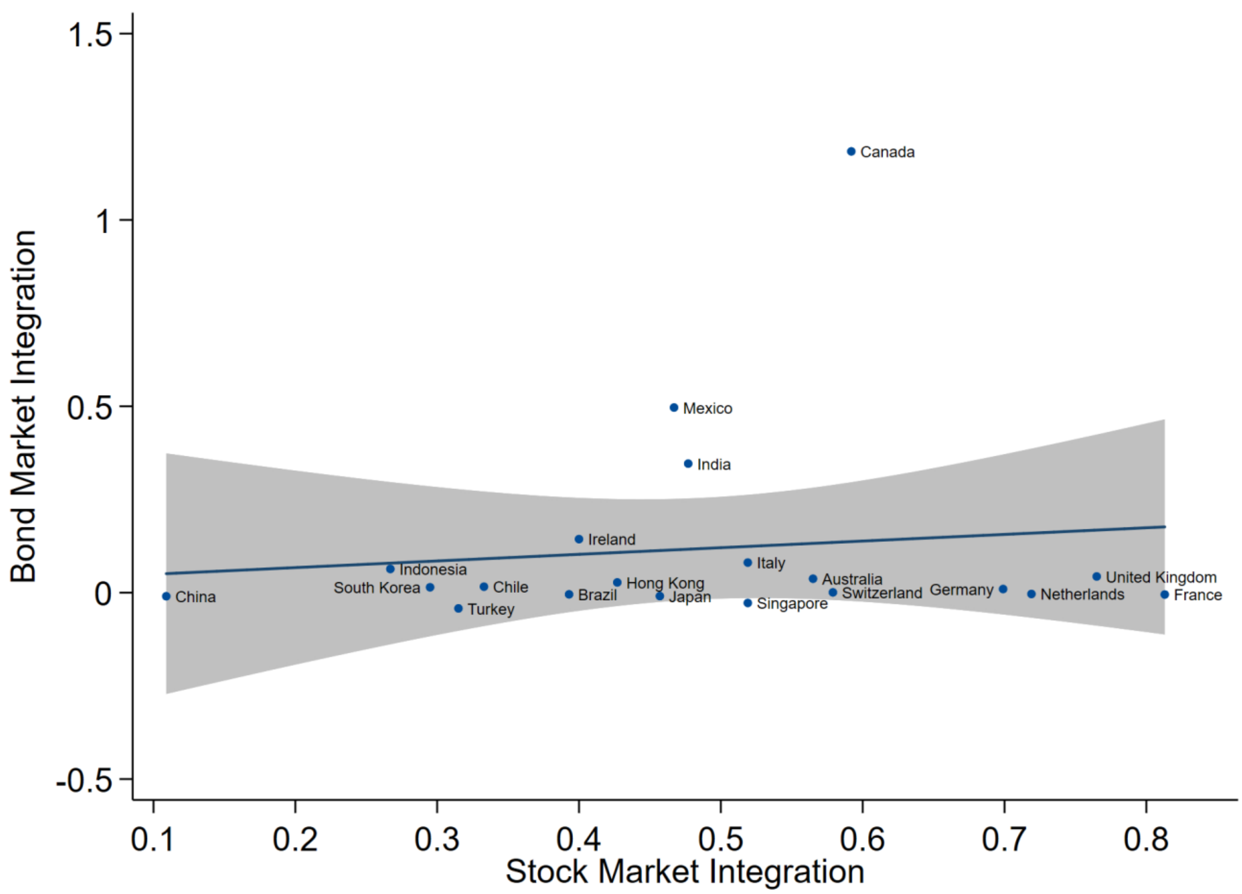

Table 2.1: Sample Distribution

This table reports sample distribution for three markets, i.e., the 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 a bond's International Securities Identification Numbers (ISIN's). *Number of obs.* indicates the number of monthly 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
U.S.	766,522 (81%)	19,103 (78%)	1,285 (58%)
Non-U.S. developed	97,758 (10%)	2,894 (12%)	302 (14%)
Emerging	81,282 (9%)	2,453 (10%)	628 (28%)
Total	945,562	24,450	2,215

Table 2.2: Descriptive Statistics

This table reports the number of bond-month observations, cross-sectional mean, median, standard deviation, and percentiles of monthly corporate bond returns, credit rating, time to maturity, age, duration, size, illiquidity, and downside risk in the U.S. market (Panel A), non-U.S. developed market (Panel B), and emerging market (Panel C). Credit ratings are reported in conventional linear numerical scores where a 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 the relative bid-ask spread to the actual spread, divided by the average of bid and ask prices. Downside risk is proxied by 5% Value-at-Risk (VaR5), i.e., the second-lowest monthly return over the past 36 trading months.

	N	Mean	Media	SD	1st	p5	p25	p75	p95	99th
Panel A: U.S.										
Bond return (%, monthly)	766,522	0.28	0.19	2.38	-5.37	-2.34	-0.56	1.05	3.07	6.33
Rating (AAA = 1, AA+ = 2, etc.)	766,522	8.44	8.04	3.09	1.82	4.68	6.34	9.80	14.64	17.50
Time to maturity (years)	766,377	9.56	6.21	9.07	0.62	1.06	3.23	14.55	25.81	31.06
Age (years)	766,298	8.00	6.28	5.75	2.08	2.36	3.86	9.57	20.96	25.31
Duration	727,672	5.48	4.00	4.58	0.21	0.50	1.72	8.67	14.51	16.55
Size	762,288	5.26	5.84	1.85	0.60	1.41	4.46	6.48	7.45	8.01
Illiquidity	760,008	0.59	0.49	0.71	0.03	0.06	0.22	0.83	1.39	2.03
Downside risk (5% VaR)	766,377	3.22	2.59	2.75	0.34	0.61	1.47	4.16	7.97	13.29
Panel B: Non-U.S. developed										
Bond return (%, monthly)	97,758	0.24	0.16	1.95	-4.37	-1.96	-0.41	0.85	2.65	5.44
Rating (AAA = 1, AA+ = 2, etc.)	97,758	7.13	6.92	3.03	1.04	3.17	5.00	8.82	12.91	16.61
Time to maturity (years)	97,748	7.26	4.74	7.76	0.57	0.80	2.20	8.37	24.37	27.48
Age (years)	97,711	6.77	5.16	4.84	2.06	2.24	3.30	8.53	17.74	23.11
Duration	94,962	4.58	3.40	4.04	0.30	0.49	1.47	6.31	13.54	15.77
Size	97,248	5.80	6.27	1.71	0.32	1.90	5.25	6.87	7.53	7.82
Illiquidity	96,872	0.47	0.35	0.49	0.03	0.05	0.16	0.67	1.23	1.92
Downside risk (5% VaR)	97,748	2.69	2.06	2.37	0.27	0.52	1.13	3.48	7.10	11.36
Panel C: Emerging										
Bond return (%, monthly)	81,282	0.30	0.26	2.80	-8.31	-2.63	-0.43	1.03	3.35	8.48
Rating (AAA = 1, AA+ = 2, etc.)	81,282	9.78	9.58	3.39	3.60	4.80	7.49	11.92	15.83	18.25
Time to maturity (years)	81,259	6.00	3.76	7.19	0.60	0.85	2.07	6.63	23.03	27.37
Age (years)	81,259	5.24	4.11	3.59	2.05	2.19	2.94	6.36	12.61	20.51
Duration	80,334	3.79	2.63	3.48	0.27	0.48	1.36	5.09	12.17	14.95
Size	81,111	6.24	6.22	0.60	4.62	5.25	5.89	6.63	7.17	7.62
Illiquidity	80,372	0.72	0.58	0.84	0.05	0.10	0.36	0.81	1.66	3.58
Downside risk (5% VaR)	81,259	3.53	2.55	3.53	0.30	0.61	1.43	4.30	9.91	19.11

Table 2.3: Prediction Performance of Machine Learning Models

This table reports the out-of-sample prediction performance (R^2_{OOS}) of machine leaning models in the U.S. market (Panel A), non-U.S. developed market (Panel B), and emerging market (Panel C). We use 20 bond characteristics and six macro variables for the non-U.S. developed market and emerging market, and 25 characteristics (excluding *USExGrowth*) for the 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 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). The L-En (N-En) model averages the forecasts of five linear (nonlinear) models including LASSO, RIDGE, ENet, PCA, and PLS (RF, GBRT, NN1, NN2, and NN3).

	LASSO	RIDGE	ENet	PCA	PLS	RF	GBRT	NN1	NN2	NN3	L-En	N-En
Panel A: U.S.												
All bonds	3.62	3.67	3.67	4.16	3.82	3.76	3.53	4.16	4.39	4.61	3.85	4.50
Investment-grade	3.82	4.27	4.02	3.92	4.30	3.52	3.20	3.41	3.12	3.04	4.13	3.56
Non-investment-grade	1.63	1.07	1.68	3.06	2.04	1.61	2.08	2.80	1.19	1.88	2.04	2.25
Panel B: Non-U.S. developed												
All bonds	4.00	2.62	4.58	4.16	4.77	2.97	2.37	3.57	3.79	3.24	4.38	3.52
Investment-grade	4.53	4.31	4.55	4.65	5.03	5.04	3.84	3.65	3.63	3.51	4.82	4.33
Non-investment-grade	1.31	0.02	-0.11	3.12	0.52	0.98	1.96	0.88	1.82	0.72	1.56	1.66
Panel C: Emerging												
All bonds	4.99	5.14	4.97	5.02	5.28	4.75	3.01	4.78	4.91	4.67	5.17	4.81
Investment-grade	4.51	2.89	4.42	5.34	3.98	1.86	2.01	3.25	3.45	3.89	4.56	3.34
Non-investment-grade	4.57	4.86	4.66	4.23	4.68	4.58	2.28	4.48	4.36	4.15	4.75	4.48

Table 2.4: Equal-weighted Performance of Machine Learning Portfolios

This table reports the out-of-sample performance of prediction-sorted portfolios in the U.S. market (Panel A), non-U.S. developed market (Panel B), and emerging market (Panel C) using 21 bond characteristics. At the end of each month, we sort bonds into deciles based on each model's one-month-ahead out-of-sample bond return predictions and construct an equal-weighted portfolio. We report the annualized Sharpe ratio of long-short portfolio and time-series average monthly 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.												
LASSO	0.06	0.10	0.20	0.23	0.28	0.37	0.49	0.59	0.74	1.15	1.09(2.48)	1.13
RIDGE	0.12	0.16	0.19	0.24	0.29	0.37	0.48	0.56	0.68	1.11	0.99(2.26)	1.14
ENet	0.08	0.12	0.19	0.21	0.29	0.40	0.48	0.60	0.72	1.12	1.05(2.35)	1.09
PCA	0.08	0.12	0.18	0.22	0.30	0.35	0.47	0.58	0.65	1.25	1.17(2.52)	1.23
PLS	0.09	0.15	0.19	0.23	0.28	0.38	0.50	0.56	0.70	1.13	1.03(2.33)	1.17
RF	0.06	0.10	0.11	0.27	0.30	0.38	0.47	0.61	0.69	1.21	1.14(2.51)	1.22
GBRT	0.37	0.24	0.27	0.25	0.25	0.28	0.26	0.37	0.75	1.18	0.82(2.10)	1.45
NN1	0.08	0.17	0.19	0.25	0.31	0.38	0.46	0.50	0.70	1.17	1.09(2.61)	1.55
NN2	0.22	0.18	0.17	0.22	0.29	0.31	0.43	0.48	0.64	1.27	1.05(2.17)	1.56
NN3	0.14	0.13	0.17	0.24	0.33	0.35	0.44	0.56	0.67	1.18	1.04(2.21)	1.39
L-En	0.07	0.13	0.19	0.22	0.28	0.39	0.49	0.59	0.70	1.15	1.08(2.41)	1.17
N-En	0.09	0.15	0.20	0.22	0.30	0.36	0.43	0.51	0.70	1.23	1.14(2.55)	1.54
Panel B: Non-U.S. developed												
LASSO	0.13	0.14	0.16	0.23	0.23	0.31	0.34	0.46	0.51	0.95	0.83(1.88)	0.90
RIDGE	0.41	0.14	0.15	0.21	0.28	0.31	0.34	0.39	0.51	0.74	0.33(1.32)	0.48
ENet	0.13	0.12	0.16	0.23	0.24	0.29	0.39	0.42	0.46	1.03	0.90(1.77)	1.19
PCA	0.07	0.10	0.13	0.21	0.23	0.28	0.37	0.42	0.60	1.05	0.97(2.47)	0.86
PLS	0.04	0.12	0.17	0.21	0.26	0.33	0.33	0.53	0.55	0.94	0.90(1.87)	1.49
RF	0.11	0.12	0.13	0.17	0.21	0.33	0.34	0.45	0.58	1.03	0.92(2.47)	0.92
GBRT	0.37	0.31	0.29	0.31	0.25	0.30	0.31	0.36	0.39	0.58	0.22(1.72)	1.16
NN1	0.11	0.16	0.09	0.19	0.27	0.28	0.38	0.51	0.56	0.94	0.84(3.11)	1.60
NN2	0.00	0.13	0.19	0.24	0.28	0.35	0.38	0.41	0.56	0.94	0.93(3.02)	1.13
NN3	0.18	0.14	0.16	0.20	0.23	0.30	0.38	0.49	0.59	0.80	0.63(2.60)	1.00
L-En	0.06	0.10	0.12	0.25	0.24	0.33	0.39	0.45	0.53	0.99	0.93(1.99)	1.41
N-En	0.06	0.10	0.16	0.21	0.26	0.31	0.38	0.44	0.54	1.00	0.94(3.49)	1.44
Panel C: Emerging												
LASSO	0.13	0.15	0.18	0.24	0.27	0.32	0.44	0.46	0.51	1.33	1.20(3.19)	1.14
RIDGE	0.22	0.23	0.17	0.24	0.28	0.30	0.39	0.34	0.52	1.33	1.11(2.67)	1.12
ENet	0.16	0.17	0.18	0.23	0.28	0.32	0.42	0.44	0.51	1.32	1.16(2.96)	1.09
PCA	0.11	0.17	0.19	0.24	0.25	0.29	0.32	0.48	0.58	1.41	1.30(3.36)	1.14

PLS	0.15	0.21	0.19	0.23	0.25	0.31	0.41	0.42	0.51	1.36	1.20(3.09)	1.14
RF	0.20	0.17	0.22	0.19	0.32	0.33	0.40	0.38	0.49	1.33	1.13(3.18)	1.03
GBRT	0.32	0.15	0.17	0.17	0.26	0.34	0.41	0.45	0.45	1.30	0.99(2.95)	1.02
NN1	0.23	0.17	0.16	0.22	0.28	0.30	0.36	0.49	0.50	1.33	1.10(2.86)	1.05
NN2	0.23	0.14	0.18	0.18	0.29	0.32	0.42	0.43	0.51	1.33	1.10(3.07)	1.07
NN3	0.18	0.19	0.21	0.18	0.23	0.33	0.34	0.45	0.67	1.27	1.09(3.10)	0.99
L-En	0.14	0.19	0.16	0.25	0.27	0.30	0.42	0.42	0.51	1.37	1.23(3.16)	1.16
N-En	0.21	0.16	0.13	0.21	0.25	0.39	0.42	0.42	0.54	1.31	1.11(3.04)	1.02

Table 2.5: Value-weighted Performance of Machine Learning Portfolios

This table reports the out-of-sample performance of prediction-sorted portfolios in the U.S. market (Panel A), non-U.S. developed market (Panel B), and emerging market (Panel C) using 21 bond characteristics. At the end of each month, we sort bonds into deciles based on each model's one-month-ahead out-of-sample bond return predictions and construct a value-weighted portfolio, using amount issued as weights. We report the annualized Sharpe ratio of long-short portfolio and time-series average monthly 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.												
LASSO	0.05	0.11	0.20	0.24	0.32	0.43	0.56	0.67	0.81	1.38	1.33(2.29)	1.20
RIDGE	0.12	0.21	0.22	0.29	0.37	0.48	0.57	0.64	0.82	1.40	1.29(2.12)	1.22
ENet	0.08	0.14	0.21	0.22	0.32	0.46	0.55	0.67	0.83	1.39	1.31(2.24)	1.18
PCA	0.10	0.14	0.19	0.25	0.35	0.41	0.55	0.66	0.79	1.46	1.35(2.24)	1.21
PLS	0.10	0.20	0.22	0.28	0.35	0.47	0.56	0.66	0.83	1.40	1.30(2.20)	1.24
RF	0.05	0.11	0.12	0.28	0.32	0.39	0.49	0.62	0.70	1.45	1.41(3.01)	1.29
GBRT	0.28	0.25	0.27	0.25	0.23	0.26	0.24	0.38	0.79	1.42	1.13(2.19)	1.52
NN1	0.08	0.17	0.21	0.29	0.37	0.45	0.53	0.70	0.76	1.44	1.37(2.72)	1.44
NN2	0.21	0.19	0.20	0.25	0.34	0.35	0.51	0.57	0.77	1.43	1.22(2.22)	1.31
NN3	0.13	0.14	0.21	0.29	0.39	0.45	0.49	0.57	0.70	1.41	1.28(2.14)	1.24
L-En	0.08	0.17	0.22	0.27	0.33	0.47	0.56	0.68	0.82	1.44	1.35(2.23)	1.23
N-En	0.12	0.16	0.22	0.27	0.35	0.42	0.54	0.64	0.74	1.44	1.32(2.50)	1.30
Panel B: Non-U.S. developed												
LASSO	0.13	0.14	0.16	0.23	0.24	0.29	0.33	0.45	0.56	0.89	0.77(2.03)	0.84
RIDGE	0.35	0.09	0.14	0.19	0.28	0.30	0.34	0.41	0.54	0.73	0.38(1.59)	0.62
ENet	0.13	0.13	0.16	0.23	0.26	0.27	0.39	0.41	0.46	0.97	0.84(1.78)	1.09
PCA	0.07	0.10	0.13	0.22	0.24	0.27	0.39	0.44	0.65	1.08	1.01(2.30)	0.90
PLS	0.05	0.12	0.19	0.24	0.25	0.33	0.34	0.50	0.58	0.98	0.92(2.02)	1.35
RF	0.09	0.12	0.13	0.16	0.24	0.36	0.37	0.42	0.54	1.02	0.93(2.44)	0.96
GBRT	0.31	0.32	0.27	0.28	0.25	0.28	0.28	0.36	0.40	0.52	0.21(1.75)	1.12
NN1	0.19	0.16	0.11	0.19	0.28	0.30	0.39	0.49	0.59	0.91	0.72(3.65)	1.21
NN2	0.00	0.11	0.20	0.25	0.32	0.35	0.41	0.42	0.66	0.97	0.97(3.19)	1.15
NN3	0.18	0.15	0.16	0.21	0.24	0.34	0.44	0.52	0.62	0.81	0.63(2.76)	0.97
L-En	0.06	0.10	0.15	0.25	0.25	0.34	0.39	0.44	0.54	0.96	0.89(2.16)	1.27
N-En	0.09	0.10	0.17	0.23	0.28	0.32	0.38	0.43	0.63	0.97	0.89(3.51)	1.25
Panel C: Emerging												
LASSO	0.11	0.13	0.15	0.23	0.29	0.32	0.45	0.52	0.60	1.32	1.21(3.05)	1.00
RIDGE	0.23	0.21	0.17	0.25	0.30	0.33	0.40	0.37	0.55	1.42	1.19(2.73)	1.03
ENet	0.15	0.15	0.17	0.23	0.29	0.34	0.43	0.50	0.60	1.32	1.17(2.86)	0.96

PCA	0.11	0.17	0.18	0.24	0.27	0.31	0.33	0.50	0.69	1.46	1.34(3.42)	1.05
PLS	0.16	0.20	0.18	0.25	0.25	0.35	0.45	0.44	0.57	1.45	1.29(3.19)	1.05
RF	0.18	0.17	0.23	0.20	0.31	0.34	0.42	0.41	0.60	1.34	1.16(3.04)	0.95
GBRT	0.31	0.14	0.17	0.18	0.27	0.36	0.41	0.49	0.54	1.30	0.99(2.68)	0.88
NN1	0.24	0.19	0.19	0.24	0.30	0.31	0.37	0.51	0.50	1.35	1.11(2.87)	0.98
NN2	0.23	0.12	0.19	0.24	0.32	0.36	0.49	0.45	0.46	1.35	1.12(3.10)	0.99
NN3	0.17	0.19	0.20	0.21	0.24	0.39	0.39	0.50	0.71	1.25	1.08(3.05)	0.89
L-En	0.13	0.19	0.15	0.26	0.29	0.32	0.45	0.46	0.57	1.43	1.30(3.20)	1.07
N-En	0.18	0.17	0.13	0.24	0.29	0.40	0.45	0.48	0.57	1.29	1.11(2.97)	0.92

Table 2.6: Prediction Performance of Machine Learning Models Using U.S. Parameters

This table reports the out-of-sample prediction performance of machine leaning models in the non-U.S. developed market (Panel A) and emerging market (Panel B) by using parameters based on the training and validation sample in the U.S. market. We use 21 bond characteristics. For each market, we report R^2_{OOS} and the change of R^2_{OOS} and profits after using U.S. parameters. Machine leaning models include 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 three layers (NN1–NN3). The L-En (N-En) model averages the forecasts of five linear (nonlinear) models including LASSO, RIDGE, ENet, PCA, and PLS (RF, GBRT, NN1, NN2, and NN3).

	LASSO	RIDGE	ENet	PCA	PLS	RF	GBRT	NN1	NN2	NN3	L-En	N-En
Panel A: Non-U.S. developed												
R^2_{OOS} U.S. parameters	2.53	2.65	2.54	2.88	3.33	4.21	4.03	1.30	2.07	3.12	2.87	3.75
R^2_{OOS} Difference	-1.47	0.03	-2.04	-1.28	-1.44	1.24	1.66	-2.26	-1.72	-0.11	-1.51	0.22
Panel B: Emerging												
R^2_{OOS} U.S. parameters	1.52	1.94	1.77	1.57	2.13	2.09	2.38	2.67	1.94	2.02	1.89	3.02
R^2_{OOS} Difference	-3.48	-3.20	-3.20	-3.45	-3.15	-2.66	-0.63	-2.11	-2.97	-2.65	-3.28	-1.79

Table 2.7: Bond Market Integration: By Market

This table reports the out-of-sample prediction performance of machine leaning models in the 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 BMKT, DEF, LRF, CRF, and DRF constructed in this paper. We finally have 21 bond characteristics and the newly added five factor exposures. For each market, we report R^2_{OOS} and the change of R^2_{OOS} after adding five U.S. factor exposures. Machine leaning models include 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 three layers (NN1–NN3). The L-En (N-En) model averages the forecasts of five linear (nonlinear) models including LASSO, RIDGE, ENet, PCA, and PLS (RF, GBRT, NN1, NN2, and NN3).

	LASSO	RIDGE	ENet	PCA	PLS	RF	GBRT	NN1	NN2	NN3	L-En	N-En
Panel A: Non-U.S. developed												
R^2_{OOS} with U.S. Factor	4.03	3.48	4.79	4.42	5.17	3.32	2.37	3.88	3.57	4.12	4.74	3.81
R^2_{OOS} Difference	0.03	0.86	0.21	0.26	0.40	0.35	0.00	0.31	-0.22	0.89	0.36	0.28
Panel B: Emerging												
R^2_{OOS} with U.S. Factor	5.33	5.26	5.28	5.32	5.53	5.61	2.73	5.02	4.37	4.66	5.48	4.92
R^2_{OOS} Difference	0.34	0.12	0.31	0.30	0.25	0.86	-0.28	0.23	-0.54	0.00	0.31	0.11

Table 2.8: Bond Market Integration: By Country

This table reports bond market integration by country and market category. Bond market integration for each is measured by the relative percentage change of R^2_{OOS} after adding the exposures to U.S. bond factors (including BMKT, DEF, LRF, CRF, and DRF) as new predictors. We train our machine learning models and make predictions for each country separately, and require at least 50 bonds for each country to have adequate observations to calculate R^2_{OOS}. Finally, we average the forecasts of 10 machine learning models to estimate R^2_{OOS}.

Developed Countries	Num of Bonds	Integration (%)	Emerging Countries	Num of Bonds	Integration (%)
Canada	590	118.39	Mexico	166	49.67
Ireland	57	14.37	India	141	34.62
Italy	80	8.08	Indonesia	55	6.36
United Kingdom	563	4.35	Chile	57	1.61
Australia	452	3.75	South Korea	139	1.45
Hong Kong	125	2.75	Brazil	234	-0.45
Germany	159	0.98	China	700	-0.96
Switzerland	58	0.08	Turkey	69	-4.22
Netherlands	70	-0.35	United Arab Emirates	101	-16.34
France	164	-0.49	Russia	97	-52.80
Japan	221	-0.92			
Singapore	54	-2.76			
DEV Mean	216	12.35	EMG Mean	176	1.89

Table 2.9: Bond-Stock Integration: By Market

This table reports the out-of-sample prediction performance of machine leaning models in the U.S. market (Panel A), non-U.S. developed market (Panel B), and emerging market (Panel C) by adding stock characteristics. We use 21 bond characteristics and 24 stock characteristics. For each market, we report R_{OOS}^2 and the change of R_{OOS}^2 after adding 24 stock characteristics. Machine leaning models include 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 three layers (NN1–NN3). The L-En (N-En) model averages the forecasts of five linear (nonlinear) models including LASSO, RIDGE, ENet, PCA, and PLS (RF, GBRT, NN1, NN2, and NN3).

	LASSO	RIDGE	ENet	PCA	PLS	RF	GBRT	NN1	NN2	NN3	L-En	N-En
Panel A: U.S.												
R_{OOS}^2 with Stock Chas	3.42	3.33	3.46	3.83	3.66	3.68	3.12	4.07	3.69	4.28	3.69	4.40
R_{OOS}^2 Difference	-0.20	-0.34	-0.21	-0.33	-0.16	-0.08	-0.41	-0.10	-0.69	-0.32	-0.16	-0.10
Panel B: Non-U.S. developed												
R_{OOS}^2 with Stock Chas	3.68	0.72	4.19	3.93	4.06	2.82	2.17	2.89	3.63	3.49	4.00	3.44
R_{OOS}^2 Difference	-0.33	-1.91	-0.39	-0.23	-0.71	-0.15	-0.20	-0.68	-0.16	0.25	-0.38	-0.08
Panel C: Emerging												
R_{OOS}^2 with Stock Chas	4.17	4.35	4.37	4.43	4.49	4.50	2.57	4.88	4.77	4.48	4.64	4.76
R_{OOS}^2 Difference	-0.82	-0.80	-0.60	-0.59	-0.79	-0.25	-0.45	0.10	-0.14	-0.19	-0.53	-0.05

Table 2.10: Bond-Stock Integration: By Country

This table reports bond-stock integration by country and market category. Bond-stock integration for each country is measured by the relative percentage change of R^2_{OOS} after adding stock characteristics as new predictors. We train our machine learning models and make predictions for each country separately, and require at least 50 bonds for each country to have adequate observations to calculate R^2_{OOS}. Finally, we average the forecasts of 10 machine learning models to estimate R^2_{OOS}.

Developed Markets	Num of Bonds	Integration (%)	Emerging Markets	Num of Bonds	Integration (%)
Canada	590	114.45	Turkey	69	30.11
Italy	80	50.28	South Korea	139	17.46
France	164	21.69	Indonesia	55	9.69
Japan	221	3.70	Chile	57	-0.87
Germany	159	2.59	Brazil	234	-12.38
Netherlands	70	0.63	United Arab Emirates	101	-23.59
Australia	452	-0.03	China	700	-67.46
Singapore	54	-2.83	Russia	97	-70.94
Hong Kong	125	-9.11	India	141	-119.50
Switzerland	58	-9.22	Mexico	166	-166.66
United Kingdom	563	-34.47			
Ireland	57	-42.05			
DEV Mean	216	7.97	EMG Mean	176	-40.42

Table 3.1. Summary Statistics

Panel A of this table provides the number of observations (N), mean, standard deviation (STD), p25 (25th percentile), median, and p75 (75th percentile) of main variables. The last two columns report the difference in mean and the t-statistics (based on a two-tailed test). Panel B of this table presents the number of observations (N), the percentage of observations for each country, along with the mean and standard deviation (STD) of *ClimateRisk* and *LnSpread* for each country. The Appendix provides the definitions for all the variables. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. Full sample

Variable	Full sample						Low climate risk		High climate risk			
	N	Mean	STD	p25	Median	p75	N	Mean	N	Mean	Difference in Mean	*t-statistics of t*-test
ClimateRisk	22665	0.09	0.29	0.00	0.00	0.00	20592	0.00	2073	1.00	1.00	-
LnSpread	22665	5.09	0.80	4.73	5.17	5.62	20592	5.06	2073	5.42	-0.37***	-20.08
LnTotalCovenant	22665	0.97	1.02	0.00	0.69	1.95	20592	0.97	2073	0.98	-0.01	-0.34
Collateral	22665	0.48	0.50	0.00	0.00	1.00	20592	0.47	2073	0.63	-0.16***	-14.25
LoanSize	22665	19.22	1.54	18.39	19.34	20.25	20592	19.27	2073	18.73	0.53***	15.07
LnMaturity	22665	3.85	0.58	3.61	4.11	4.11	20592	3.85	2073	3.91	-0.06***	-4.60
PerformancePricing	22665	0.33	0.47	0.00	0.00	1.00	20592	0.34	2073	0.26	0.08***	7.35
LoanPurpose	22665	14.81	14.23	6.00	6.00	26.00	20592	14.88	2073	14.15	0.72**	2.20
LoanType	22665	36.90	12.35	38.00	38.00	45.00	20592	36.63	2073	39.59	-2.96***	-10.43
ClimateRiskDisclosure	15486	1.35	9.22	0.00	0.00	0.00	14196	1.36	1290	1.23	0.13	0.48
FirmSize	22665	7.82	1.70	6.60	7.73	8.93	20592	7.88	2073	7.13	0.75***	19.28
Profitability	22665	0.13	0.07	0.09	0.13	0.17	20592	0.14	2073	0.12	0.01***	7.87
Leverage	22665	0.32	0.20	0.18	0.29	0.43	20592	0.32	2073	0.37	-0.06***	-12.28
Tangibility	22665	0.29	0.22	0.11	0.22	0.41	20592	0.29	2073	0.30	-0.01**	-2.49
MB	22665	2.51	3.27	1.06	1.74	2.93	20592	2.52	2073	2.36	0.16**	2.15
CashFlowVolatility	22665	0.62	2.40	0.07	0.13	0.25	20592	0.60	2073	0.74	-0.13**	-2.43
Z-score	22665	1.60	1.16	0.87	1.55	2.30	20592	1.63	2073	1.22	0.42***	15.68
Rating	22665	15.57	6.59	10.00	14.00	23.00	20592	15.31	2073	18.18	-2.87***	-19.06
GDPGrowth	22665	2.26	1.41	1.70	2.29	2.80	20592	2.27	2073	2.19	0.08**	2.33

Panel B. Country-level summary statistics						
Country	N	N (%)	*ClimateRisk* Mean	*ClimateRisk* STD	*LnSpread* Mean	*LnSpread* STD
Australia	283	1.25%	0.04	0.20	5.12	0.61
Austria	19	0.08%	0.16	0.37	4.30	0.73
Belgium	39	0.17%	0.18	0.39	5.05	0.94
Brazil	97	0.43%	0.24	0.43	4.96	0.68
Chile	21	0.09%	0.10	0.30	4.85	0.80
China	20	0.09%	0.25	0.44	5.65	0.45
Denmark	58	0.26%	0.03	0.18	5.37	0.76
Finland	43	0.19%	0.19	0.39	4.37	1.07
France	447	1.97%	0.08	0.27	4.85	0.95
Germany	558	2.46%	0.08	0.26	4.74	1.00
Greece	18	0.08%	0.00	0.00	4.67	1.28
Hong Kong	93	0.41%	0.05	0.23	4.55	0.80
India	63	0.28%	0.03	0.18	5.32	0.73
Ireland	23	0.10%	0.04	0.21	5.21	0.83
Israel	23	0.10%	0.04	0.21	5.22	0.86
Italy	136	0.60%	0.16	0.37	4.98	0.83
Japan	328	1.45%	0.17	0.37	4.43	1.05
South Korea	42	0.19%	0.00	0.00	5.03	0.44
Malaysia	23	0.10%	0.04	0.21	5.07	0.57
Mexico	62	0.27%	0.18	0.39	5.09	0.75
Netherlands	230	1.01%	0.20	0.40	5.27	0.92
New Zealand	16	0.07%	0.38	0.50	4.67	0.70
Norway	99	0.44%	0.06	0.24	5.22	0.78
Poland	23	0.10%	0.09	0.29	4.94	0.84
Russian	120	0.53%	0.00	0.00	5.22	0.63
Saudi Arabia	11	0.05%	0.00	0.00	4.67	0.71
Singapore	27	0.12%	0.04	0.19	4.69	0.88
South Africa	52	0.23%	0.08	0.27	5.11	0.70
Spain	130	0.57%	0.10	0.30	5.39	0.72
Sweden	113	0.50%	0.12	0.32	4.39	1.06
Switzerland	153	0.68%	0.23	0.42	4.62	1.24
Thailand	7	0.03%	0.71	0.49	4.47	0.93
Turkey	41	0.18%	0.00	0.00	5.21	0.72
United Kingdom	1036	4.57%	0.13	0.34	5.12	0.81
U.S.	18211	80.35%	0.09	0.28	5.13	0.76

Table 3.2: Pearson Correlation Matrix of the Variables

This table presents the Pearson correlation matrix of all variables. The Appendix provides the definitions of all the variables. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively

Variable	*ClimateRisk*	*LnSpread*	*LnTotalCovenant*	*Collateral*	*LoanSize*	*LnMaturity*	*PerformancePricing*	*LoanPurpose*	*LoanType*
1. ClimateRisk	1								
2. LnSpread	0.13***	1							
3. LnTotalCovenant	0.00	0.11***	1						
4. Collateral	0.09***	0.50***	0.36***	1					
5. LoanSize	-0.10***	-0.34***	-0.06***	-0.18***	1				
6. LnMaturity	0.03***	0.23***	0.03***	0.24***	0.00	1			
7. PerformancePricing	-0.05***	-0.12***	0.56***	0.07***	0.04***	-0.02***	1		
8. LoanPurpose	-0.02**	0.10***	0.26***	0.17***	-0.05***	0.03***	0.23***	1	
9. LoanType	0.07***	0.37***	0.07***	0.28***	-0.14***	0.64***	-0.06***	0.023***	1
10. ClimateRiskDisclosure	-0.00	0.00	-0.01	0.00	-0.02*	0.01	0.00300	0.00	0.02**
11. FirmSize	-0.14***	-0.37***	-0.29***	-0.29***	0.54***	-0.08***	-0.13***	-0.15***	-0.18***
12. Profitability	-0.05***	-0.22***	0.02***	-0.13***	0.12***	0.00	0.09***	0.02***	-0.07***
13. Leverage	0.08***	0.24***	0.04***	0.23***	0.01	0.06***	-0.09***	-0.06***	0.11***
14. Tangibility	0.02**	-0.01	0.01	0.00	0.03***	-0.03***	0.01	-0.01*	-0.02***
15. MB	-0.01**	-0.11***	-0.04***	-0.09***	0.08***	-0.03***	-0.00	-0.02**	-0.08***
16. CashFlowVolatility	0.02**	-0.03***	0.01**	0.00	-0.06***	0.01*	0.02***	0.05***	0.00
17. Z-score	-0.10***	-0.26***	0.01**	-0.16***	0.02**	-0.05***	0.11***	0.05***	-0.11***
18. Rating	0.13***	0.37***	0.10***	0.20***	-0.37***	0.10***	-0.02***	0.08***	0.23***
19. GDPGrowth	-0.02**	-0.12***	0.05***	0.01**	-0.02***	0.06***	0.03***	0.00	0.01

Table 3.2-*Continued*

Variable	*ClimateRiskDisclosure*	*FirmSize*	*Profitability*	*Leverage*	*Tangibility*	*MB*	*CashFlowVolatility*	*Z-score*	*Rating*	*GDPGrowth*
10. ClimateRiskDisclosure	1									
11. FirmSize	-0.01*	1								
12. Profitability	0.01	-0.01	1							
13. Leverage	0.00	0.01	-0.03***	1						
14. Tangibility	0.03***	0.05***	0.11***	0.17***	1					
15. MB	-0.01	0.06***	0.26***	-0.02**	-0.06***	1				
16. CashFlowVolatility	-0.00	-0.13***	0.08***	-0.30***	-0.08***	0.02***	1			
17. Z-score	0.01	-0.04***	0.40***	-0.45***	-0.17***	0.12***	0.14***	1		
18. Rating	-0.01	-0.64***	-0.15***	-0.05***	-0.05***	-0.10***	0.14***	-0.05***	1	
19. GDPGrowth	0.00	-0.05***	0.01*	0.01	0.04***	-0.01*	-0.00	0.01*	-0.03***	1

Table 3.3: Climate Risk, Firm Performance, and Credit Rating

This table reports the effect of climate risk on financial performance and credit risk. The dependent variables are cash flows from operations (*CFO*) (column 1), return-on-assets (*ROA*) (column 2) and credit ratings (*Rating*) (column 3). *ClimateRisk* is an indicator variable that equals 1 if the annual average absolute value of the return sensitivity to temperature anomaly of a firm is in the highest quintile in its home country in a year, and 0 otherwise. The Appendix provides definitions for all variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
	CFO_{t+1}	ROA_{t+1}	$Rating_{t+1}$
ClimateRisk	-0.006**	-0.025***	0.402**
	(-2.331)	(-3.682)	(2.528)
FirmSize	0.001*	0.007***	-2.850***
	(1.651)	(4.653)	(-57.381)
Profitability	0.484***	0.608***	-10.450***
	(28.296)	(17.450)	(-9.560)
Leverage	-0.017***	-0.011	-1.723***
	(-3.123)	(-1.090)	(-3.718)
Tangibility	0.028***	-0.043***	1.117**
	(6.152)	(-4.709)	(2.461)
MB	0.002***	0.001**	-0.066***
	(6.011)	(2.497)	(-3.740)
CashFlowVolatility	0.000	0.001	0.126***
	(0.413)	(1.336)	(5.241)
Z-score	-0.001	0.013***	-0.066
	(-0.442)	(6.137)	(-0.703)
Rating	-0.000	-0.000	
	(-1.605)	(-1.509)	
GDPGrowth	-0.001	0.003**	0.113
	(-0.675)	(2.575)	(1.595)
Constant	-0.005	-0.130***	38.988***
	(-0.300)	(-4.577)	(35.130)
Year effect	Yes	Yes	Yes
Country effect	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes
Observations	11,653	11,664	13,128
Adj. R^2	0.315	0.213	0.525

Table 3.4: The Effect of Climate Risk on the Cost of Bank Loans

This table reports the regression results of testing the effect of climate risk on loan spread. Column (1) does not include control variables, column (2) includes firm and macro variables, column (3) adds loan specific variables, and column (4) further controls for bank fixed effects. *ClimateRisk* is an indicator variable that equals 1 if the annual average absolute value of the return sensitivity to temperature anomaly of a firm is in the highest quintile in its home country in a year, and 0 otherwise. The Appendix provides the definitions for all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	LnSpread	*LnSpread*	*LnSpread*	*LnSpread*
ClimateRisk	0.365***	0.082***	0.068***	0.064***
	(20.078)	(3.758)	(3.981)	(3.911)
FirmSize		-0.162***	-0.056***	-0.051***
		(-19.351)	(-7.818)	(-7.068)
Profitability		-1.530***	-1.102***	-1.040***
		(-10.799)	(-10.746)	(-10.429)
Leverage		0.723***	0.369***	0.358***
		(14.755)	(9.970)	(9.855)
Tangibility		-0.174***	-0.031	-0.029
		(-3.590)	(-0.876)	(-0.857)
MB		-0.008***	-0.003	-0.004**
		(-2.617)	(-1.329)	(-2.265)
CashFlowVolatility		0.003	-0.004*	-0.003
		(0.849)	(-1.812)	(-1.464)
Z-score		-0.081***	-0.052***	-0.054***
		(-7.393)	(-6.863)	(-7.201)
Rating		0.012***	0.009***	0.010***
		(6.125)	(7.383)	(7.839)
LoanSize			-0.100***	-0.097***
			(-13.099)	(-13.742)
LnMaturity			-0.027*	-0.020
			(-1.681)	(-1.272)
LnTotalCovenant			0.011*	0.014**
			(1.737)	(2.174)
Collateral			0.341***	0.313***
			(23.037)	(23.004)

PerformancePricing			-0.070***	-0.061***
			(-5.882)	(-5.171)
GDPGrowth		-0.019	-0.027***	-0.017*
		(-1.431)	(-2.742)	(-1.695)
Constant	5.059***	6.184***	7.166***	7.485***
	(920.162)	(33.511)	(41.019)	(44.571)
LoanType	No	No	Yes	Yes
LoanPurpose	No	No	Yes	Yes
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes
Observations	22,665	22,665	22,665	22,665
Adj. R^2	0.017	0.413	0.653	0.678

Table 3.5: Robustness and "Placebo" Tests

This table reports the robustness test and "placebo" test results. Panel A reports robustness test for a reduced sample excluding U.S. firms; Panel B reports the robustness test using the PSM sample; Panel C reports the robustness test using an alternative measure of temperature anomaly to construct *ClimateRisk*; and Panel D reports the "placebo" test results for sample periods of 1992 to 1999. In Panels A, B, and D**,** *ClimateRisk* is an indicator variable that equals 1 if the annual average absolute value of the return sensitivity to temperature anomaly of a firm is in the highest quintile in its home country in a year, and 0 otherwise. In Panel C, *ClimateRisk2* is constructed based on a new temperature anomaly that is measured by the deviation from the average temperature of a particular month over the past 30 years in a firm's home country (i.e., using a rolling past 30-year window instead of using the fixed benchmark window of 1951-1980 in Eq. (1). Column (2) further controls for bank fixed effects compared to column (1). The Appendix provides the definitions of all other variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Non-U.S. sample		
	(1)	(2)
	LnSpread	*LnSpread*
ClimateRisk	0.166***	0.149***
	(3.629)	(3.179)
Controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Bank FE	No	Yes
Observations	20,479	20,479
Adj. R^2	0.660	0.686
Panel B: PSM sample		
ClimateRisk	0.085***	0.102***
	(4.035)	(4.533)
Controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Bank FE	No	Yes
Observations	4,454	4,454
Adj. R^2	0.621	0.666
Panel C: Using an alternative measure of temperature anomaly to construct *ClimateRisk*		
ClimateRisk2	0.075***	0.068***
	(4.345)	(4.118)
Controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes

Industry FE	Yes	Yes
Bank FE	No	Yes
Observations	22,665	22,665
Adj. R^2	0.653	0.679
Panel D: "Placebo" test: sample period before the twenty-first century (1992-1999)		
ClimateRisk	0.013	0.018
	(0.472)	(0.667)
Controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Bank FE	No	Yes
Observations	4,679	4,679
Adj. R^2	0.698	0.721

Table 3.6: Loan Maturity and Climate Risk

This table reports the regression results of testing the moderating effect of loan maturity on the relation between climate risk on loan spread. Column (2) further controls for bank fixed effects compared to column (1). *ClimateRisk* is an indicator variable that equals 1 if the annual average absolute value of the return sensitivity to temperature anomaly of a firm is in the highest quintile in its home country in a year, and 0 otherwise. The Appendix provides the definitions for all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
	LnSpread	*LnSpread*
*ClimateRisk*LnMaturity*	-0.060*	-0.074**
	(-1.879)	(-2.299)
ClimateRisk	0.303**	0.354***
	(2.409)	(2.788)
LnMaturity	-0.020	-0.012
	(-1.269)	(-0.772)
Other controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Bank FE	No	Yes
Observations	22,665	22,665
Adj. R^2	0.653	0.679

Table 3.7: Moderating Effect of Climate Risk Disclosures

Panel A of this table reports the moderating effect of climate risk disclosures on the relation between climate risk and loan spread for full sample without bank fixed effect (column 1) and with bank fixed effect (column 2), respectively. Panel B reports the moderating effect of climate risk disclosures for the US sample (column 1) and non-US sample (column 2), respectively. *ClimateRisk* is an indicator variable that equals 1 if the annual average absolute value of the return sensitivity to temperature anomaly of a firm is in the highest quintile in its home country in a year, and 0 otherwise. *ClimateRiskDisclosure* equals 100000 times "$CCExposure^{Phy}$" from Sautner et al. (2023a), which is the percentage of physical shocks related climate change bigrams appearing in the transcripts of analyst conference. The Appendix provides the definitions for all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Full sample	(1)	(2)
	LnSpread	*LnSpread*
*ClimateRisk*ClimateRiskDisclosure*	-0.013***	-0.013***
	(-2.586)	(-2.957)
ClimateRisk	0.072***	0.062***
	(3.484)	(3.200)
ClimateRiskDisclosure	-0.001	0.001
	(-0.480)	(0.314)
Controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Bank FE	No	Yes
Observations	15,331	15,331
Adj. R^2	0.660	0.685

Panel B: U.S. and non-U.S. samples	US	non-US
ClimateRisk ClimateRiskDisclosure*	-0.010**	-0.061**
	(-2.113)	(-2.352)
ClimateRisk	0.078***	0.107
	(4.524)	(1.394)
ClimateRiskDisclosure	-0.000	0.004
	(-0.265)	(0.358)
Controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Bank FE	Yes	Yes
Observations	13,024	2,307
Adj. R^2	0.667	0.639

Table 3.8: Moderating Effect of Climate Risk Disclosures: Lead Banks with High or Low Past Climate-risk-related Lending Experience

This table reports the moderating effect of climate risk disclosures on the relation between climate risk and loan spread for loans obtained from lead banks with less and more past climate-risk-related lending experience, respectively. Columns (3) and (4) further control for bank fixed effects compared to columns (1) and (2). *ClimateRisk* is an indicator variable, which equals 1 if the annual average absolute value of the return sensitivity to temperature anomaly of a firm is in the highest quintile in its home country in a year, and 0 otherwise. *ClimateRiskDisclosure* equals 100000 times "$CCExposure^{Phy}$" from Sautner et al. (2023a), which is the percentage of physical-shock-related climate change bigrams appearing in the transcripts of analyst conference calls. When the sum of each lead bank's past climate-risk-related lending experience for a loan facility is above (below) the median, the observation is assigned to high (low) experience group. The Appendix provides the definitions for all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	LnSpread	*LnSpread*	*LnSpread*	*LnSpread*
	Low Experience	High Experience	Low Experience	High Experience
*ClimateRisk*ClimateRiskDisclosure*	-0.017***	-0.008	-0.018***	-0.009
	(-3.001)	(-1.068)	(-3.042)	(-1.421)
ClimateRisk	0.084***	0.061**	0.076***	0.056**
	(3.263)	(2.440)	(2.960)	(2.365)
ClimateRiskDisclosure	0.003	-0.005**	0.005**	-0.004*
	(1.422)	(-2.205)	(2.175)	(-1.863)
Controls	Yes	Yes	Yes	Yes
LoanType	Yes	Yes	Yes	Yes
LoanPurpose	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes
Observations	6,935	8,396	6,935	8,396
Adj. R^2	0.672	0.670	0.702	0.698

Table 3.9: Country-level Climate Information Disclosure Policy Shocks

This table reports the regression results of testing the moderating effect of SEC climate risk disclosure policy in the U.S. (Panel A) and mandatory ESG disclosure in 19 non-U.S. countries (Panel B) on the relation between climate risk and loan spread. Column (2) further controls for bank fixed effects compared to column (1). *ClimateRisk* is an indicator variable that equals 1 if the annual average absolute value of the return sensitivity to temperature anomaly of a firm is in the highest quintile in its home country in a year, and 0 otherwise. *PostYear2010* is an indicator variable that equals 1 if a loan facility to a U.S. firm starts after the 2010 SEC guidance on climate risk disclosures, and 0 otherwise. *MandataryESG* is an indicator variable that equals 1 if a loan facility starts after the borrower's home country introduced mandatory ESG disclosure, and 0 otherwise. The Appendix provides the definitions for all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
	LnSpread	*LnSpread*
Panel A: SEC climate risk disclosure guidance (U.S. sample)		
ClimateRisk PostYear2010*	-0.127***	-0.127***
	(-4.391)	(-4.546)
ClimateRisk	0.103***	0.105***
	(4.790)	(4.901)
PostYear2010	0.245***	0.234***
	(4.676)	(4.331)
Controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Bank FE	No	Yes
Observations	18,211	18,211
Adj. R^2	0.681	0.701
Panel B: ESG disclosure policy (19 non-U.S. countries)		
ClimateRisk MandataryESG*	-0.052	-0.024
	(-0.489)	(-0.217)
ClimateRisk	0.179**	0.166**
	(2.511)	(2.253)
MandataryESG	-0.029	-0.079
	(-0.467)	(-1.230)
Controls	Yes	Yes
LoanType	Yes	Yes
LoanPurpose	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Bank FE	No	Yes
Observations	2,898	2,898
Adj. R^2	0.651	0.692

Table 4.1: Descriptive Statistics

This table provides descriptive statistics of key variables. The Appendix provides the definitions of all the variables.

	N	Mean	Media	SD	p25	p75
FERROR	31006	0.0154	0.0030	0.0564	0.0012	0.0084
DISPERSION	31006	0.0129	0.0027	0.0400	0.0010	0.0081
CCExposure	31006	0.0876	0.0256	0.2279	0.0092	0.0638
$CCExposure^{Phy}$	31006	0.0013	0.0000	0.0096	0.0000	0.0000
$CCExposure^{Reg}$	31006	0.0046	0.0000	0.0235	0.0000	0.0000
$CCExposure^{Opp}$	31006	0.0348	0.0072	0.1176	0.0000	0.0219
FHORIZON	31006	97.9688	98.0000	40.5970	87.0000	112.0000
ANANO	31006	2.4074	2.3979	0.5961	1.9459	2.8904
SIZE	31006	7.4340	7.3459	1.8605	6.0791	8.6474
LOSS	31006	0.2267	0.0000	0.4187	0.0000	0.0000
ROAVOL	31006	0.0714	0.0316	0.1168	0.0138	0.0760
LEV	31006	0.1837	0.1476	0.1786	0.0150	0.2980
RD	31006	0.5665	1.0000	0.4956	0.0000	1.0000
BM	31006	0.5629	0.4631	0.4261	0.2672	0.7431

Table 4.2: The Effects of Climate Risk Disclosures on Analyst Forecast Errors and Dispersion

This table reports the regression results testing the effects of climate risk disclosure on analyst forecast errors and dispersion. *CCExposure* is an aggregate measure of climate risk disclosure, which is the percentage of bigrams related to climate change occurring in the transcripts of earnings conference calls. $CCExposure^{Phy}$, $CCExposure^{Reg}$, and $CCExposure^{Opp}$ are the percentage of bigrams capturing physical shocks, regulatory shocks and opportunities related to climate change occurring in the transcripts of earnings conference calls, respectively (Sautner et al., 2023a). The Appendix provides the definitions of all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
	FERROR	*DISPERSION*	*FERROR*	*DISPERSION*	*FERROR*	*DISPERSION*	*FERROR*	*DISPERSION*
CCExposure	0.0012	0.0003						
	(0.53)	(0.18)						
$CCExposure^{Phy}$			-0.0394**	-0.0171				
			(-2.01)	(-1.08)				
$CCExposure^{Reg}$					-0.0053	-0.0074		
					(-0.39)	(-0.75)		
$CCExposure^{Opp}$							0.0035	0.0018
							(1.04)	(0.65)
FHORIZON	0.0002***	0.0001***	0.0002***	0.0001***	0.0002***	0.0001***	0.0002***	0.0001***
	(11.44)	(10.49)	(11.46)	(10.49)	(11.46)	(10.49)	(11.44)	(10.48)
ANANO	-0.0008	0.0015*	-0.0008	0.0015*	-0.0008	0.0015*	-0.0008	0.0015*
	(-0.74)	(1.80)	(-0.75)	(1.80)	(-0.73)	(1.81)	(-0.74)	(1.80)
SIZE	-0.0012***	-0.0014***	-0.0012***	-0.0014***	-0.0012***	-0.0014***	-0.0012***	-0.0014***
	(-2.85)	(-4.79)	(-2.86)	(-4.80)	(-2.85)	(-4.79)	(-2.85)	(-4.79)
LOSS	0.0169***	0.0129***	0.0169***	0.0130***	0.0169***	0.0130***	0.0169***	0.0129***
	(13.56)	(14.46)	(13.56)	(14.45)	(13.56)	(14.46)	(13.55)	(14.45)
ROAVOL	0.0384***	0.0337***	0.0384***	0.0337***	0.0384***	0.0337***	0.0384***	0.0337***
	(7.50)	(8.86)	(7.49)	(8.86)	(7.50)	(8.86)	(7.49)	(8.86)
LEV	0.0247***	0.0209***	0.0247***	0.0209***	0.0247***	0.0209***	0.0247***	0.0210***
	(7.41)	(9.00)	(7.41)	(9.00)	(7.40)	(8.99)	(7.41)	(9.00)
RD	-0.0002	-0.0006	-0.0002	-0.0006	-0.0002	-0.0006	-0.0002	-0.0006
	(-0.22)	(-0.79)	(-0.24)	(-0.80)	(-0.24)	(-0.81)	(-0.22)	(-0.79)
BM	0.0279***	0.0231***	0.0279***	0.0231***	0.0279***	0.0231***	0.0279***	0.0231***
	(14.91)	(17.29)	(14.91)	(17.29)	(14.92)	(17.30)	(14.92)	(17.30)
Constant	-0.0373***	-0.0242***	-0.0372***	-0.0241***	-0.0373***	-0.0242***	-0.0372***	-0.0241***
	(-5.94)	(-4.58)	(-5.93)	(-4.57)	(-5.94)	(-4.58)	(-5.92)	(-4.57)
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	31,006	31,006	31,006	31,006	31,006	31,006	31,006	31,006
Adj. R-squared	0.144	0.168	0.144	0.168	0.144	0.168	0.144	0.168

Table 4.3: Subsample Analysis: Before and After the 2010 SEC's Guidance on Climate Risk Disclosures

This table reports the regression results of testing the effects of the disclosures of physical shocks related to climate change on analyst forecast errors and dispersion before and after the 2010 SEC's guidance on disclosures of climate risks and opportunities in 10-K filings. $CCExposure^{Phy}$ is the percentage of bigrams capturing physical shocks related to climate change occurring in the transcripts of earnings conference calls (Sautner et al., 2023a). The Appendix provides the definitions of all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	2002 to 2010	2011 to 2019	2002 to 2010	2011 to 2019
	FERROR	*FERROR*	*DISPERSION*	*DISPERSION*
$CCExposure^{Phy}$	-0.0189	-0.0572***	0.0060	-0.0344**
	(-0.50)	(-2.83)	(0.19)	(-2.28)
FHORIZON	0.0002***	0.0002***	0.0001***	0.0001***
	(7.82)	(8.64)	(6.67)	(8.64)
ANANO	-0.0020	-0.0006	0.0010	0.0013
	(-1.62)	(-0.38)	(1.08)	(1.15)
SIZE	-0.0003	-0.0019***	-0.0007**	-0.0019***
	(-0.51)	(-3.51)	(-2.02)	(-4.69)
LOSS	0.0173***	0.0154***	0.0126***	0.0124***
	(9.61)	(9.44)	(10.37)	(10.13)
ROAVOL	0.0236***	0.0460***	0.0210***	0.0413***
	(4.40)	(5.56)	(5.72)	(6.54)
LEV	0.0169***	0.0301***	0.0146***	0.0256***
	(3.78)	(6.79)	(4.90)	(8.19)
RD	0.0018	-0.0018	0.0008	-0.0016
	(1.30)	(-1.28)	(0.93)	(-1.55)
BM	0.0241***	0.0299***	0.0191***	0.0253***
	(10.62)	(11.04)	(11.88)	(13.04)
Constant	-0.0372***	-0.0250***	-0.0242***	-0.0152*
	(-6.37)	(-2.74)	(-6.58)	(-1.85)
year effect	yes	yes	yes	yes
industry effect	yes	yes	yes	yes
Observations	14,390	16,616	14,390	16,616
Adj R-squared	0.131	0.176	0.144	0.207

Table 4.4: Subsample Analysis: Industry Sensitivity to Climate Change

This table reports the regression results of testing the effects of disclosures of physical shocks related to climate change on analyst forecast errors and dispersion for two sets of subsamples: subsamples in industries with high sensitivity to climate change and subsamples in industries with low sensitivity to climate change. Following Kim et al. (2022), high-sensitivity industries include agriculture (Fama-French industry code 1), automobile and trucks (code 23), business services (code 34), communication (code 32), construction (code 18), energy [mines (code 28), coal (code 29), and oil (code 30)], health care (code 11), pharmaceutical products (code 13), and transportation (code 40), and other industries are low-sensitivity industries. $CCExposure^{Phy}$ is the percentage of bigrams capturing physical shocks related to climate change occurring in the transcripts of earnings conference calls (Sautner et al., 2023a). The Appendix provides the definitions of all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Low Sensitivity	High Sensitivity	Low Sensitivity	High Sensitivity
	FERROR	*FERROR*	*DISPERSION*	*DISPERSION*
$CCExposure^{Phy}$	-0.0193	-0.1782**	-0.0036	-0.1133*
	(-1.11)	(-2.21)	(-0.25)	(-1.71)
FHORIZON	0.0002***	0.0003***	0.0001***	0.0002***
	(7.66)	(8.55)	(6.81)	(7.96)
ANANO	-0.0014	-0.0004	0.0012	0.0015
	(-1.15)	(-0.19)	(1.34)	(0.92)
SIZE	-0.0006	-0.0017**	-0.0011***	-0.0017***
	(-1.37)	(-2.25)	(-3.39)	(-2.87)
LOSS	0.0171***	0.0170***	0.0129***	0.0136***
	(10.84)	(8.63)	(11.34)	(9.33)
ROAVOL	0.0364***	0.0378***	0.0297***	0.0354***
	(5.22)	(5.31)	(5.98)	(6.57)
LEV	0.0211***	0.0292***	0.0171***	0.0259***
	(5.28)	(5.01)	(6.28)	(6.20)
RD	-0.0005	-0.0002	-0.0003	-0.0015
	(-0.46)	(-0.09)	(-0.31)	(-1.09)
BM	0.0221***	0.0369***	0.0187***	0.0298***
	(12.29)	(9.17)	(14.04)	(10.65)
Constant	-0.0275***	-0.0574***	-0.0180***	-0.0397***
	(-5.69)	(-6.04)	(-5.84)	(-5.66)
Controls	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Observations	20,897	10,109	20,897	10,109
Adj. R-squared	0.129	0.161	0.144	0.187

Table 4.5: Subsample Analysis: Extreme Weather Events

This table reports the regression results of testing the effects of disclosures of physical shocks related to climate change on analyst forecast errors and dispersion for two sets of subsamples: subsamples located in regions with high versus low level of climate extremes (Panel A) and subsamples located in regions with high versus low level of climate disaster costs (Panel B). The Climate Extremes Index (CEI) and disaster costs (Billion-Dollar Weather and Climate Disasters) data are obtained from the U.S. National Oceanic and Atmospheric Administration. $CCExposure^{Phy}$ is the percentage of bigrams capturing physical shocks related to climate change occurring in the transcripts of earnings conference calls (Sautner et al., 2023a). The Appendix provides the definitions of all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	FERROR	*FERROR*	*DISPERSION*	*DISPERSION*
Panel A: CEI				
	Low CEI	High CEI	Low CEI	High CEI
$CCExposure^{Phy}$	-0.0108	-0.0584***	0.0173	-0.0390***
	(-0.27)	(-3.16)	(0.52)	(-2.95)
FHORIZON	0.0002***	0.0002***	0.0001***	0.0001***
	(8.04)	(7.77)	(7.10)	(7.64)
ANANO	-0.0011	-0.0007	0.0014	0.0011
	(-0.81)	(-0.42)	(1.50)	(1.04)
SIZE	-0.0009*	-0.0015***	-0.0012***	-0.0017***
	(-1.76)	(-2.61)	(-3.15)	(-4.41)
LOSS	0.0160***	0.0187***	0.0122***	0.0139***
	(8.92)	(11.28)	(9.78)	(11.64)
ROAVOL	0.0357***	0.0347***	0.0289***	0.0325***
	(5.37)	(4.95)	(6.08)	(6.18)
LEV	0.0309***	0.0200***	0.0244***	0.0182***
	(6.22)	(5.08)	(7.39)	(6.56)
RD	0.0011	-0.0003	0.0003	-0.0004
	(0.81)	(-0.24)	(0.31)	(-0.38)
BM	0.0244***	0.0285***	0.0198***	0.0229***
	(10.68)	(10.08)	(12.21)	(11.27)
Constant	-0.0346***	-0.0265***	-0.0210***	-0.0160*
	(-5.39)	(-2.97)	(-4.65)	(-1.68)
Year fixed effects	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Observations	14,160	14,069	14,160	14,069
Adj. R-squared	0.132	0.141	0.150	0.166
Panel B: disaster costs				
	Low Costs	High Costs	Low Costs	High Costs
$CCExposure^{Phy}$	-0.0272	-0.0587***	-0.0064	-0.0331*
	(-1.01)	(-2.64)	(-0.29)	(-1.92)
FHORIZON	0.0002***	0.0002***	0.0001***	0.0001***
	(8.12)	(7.68)	(7.50)	(7.28)
ANANO	-0.0005	-0.0011	0.0018*	0.0009
	(-0.34)	(-0.72)	(1.89)	(0.74)
SIZE	-0.0008	-0.0016***	-0.0013***	-0.0016***
	(-1.41)	(-3.06)	(-3.41)	(-4.08)
LOSS	0.0168***	0.0182***	0.0125***	0.0140***
	(9.82)	(10.37)	(10.77)	(11.05)
ROAVOL	0.0315***	0.0412***	0.0250***	0.0386***

	(5.44)	(5.07)	(6.13)	(6.55)
LEV	0.0247***	0.0247***	0.0188***	0.0229***
	(5.16)	(5.61)	(6.11)	(7.30)
RD	0.0020	-0.0011	0.0006	-0.0007
	(1.41)	(-0.90)	(0.63)	(-0.77)
BM	0.0304***	0.0230***	0.0231***	0.0197***
	(10.72)	(10.48)	(11.51)	(12.15)
Constant	-0.0429***	-0.0228**	-0.0274***	-0.0114
	(-7.00)	(-2.16)	(-5.97)	(-1.13)
Year fixed effects	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Observations	14,408	13,821	14,408	13,821
Adj. R-squared	0.135	0.140	0.151	0.167

Table 4.6: Subsample Analysis: Beliefs on Global Warming

This table reports the regression results of testing the effects of the disclosures of physical shocks related to climate change on analyst forecast errors and dispersion for subsamples located in states with high versus low level of beliefs in climate change. The climate belief data is available from 2008, obtained from the Yale Program on Climate Change Communication. $CCExposure^{Phy}$ is the percentage of bigrams capturing physical shocks related to climate change occurring in the transcripts of earnings conference calls (Sautner et al., 2022a). The Appendix provides the definitions of all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Low beliefs	High beliefs	Low beliefs	High beliefs
	FERROR	*FERROR*	*DISPERSION*	*DISPERSION*
$CCExposure^{Phy}$	-0.0299	-0.0747**	-0.0044	-0.0541***
	(-1.43)	(-2.28)	(-0.22)	(-2.69)
FHORIZON	0.0002***	0.0002***	0.0001***	0.0001***
	(7.28)	(8.29)	(6.90)	(7.57)
ANANO	-0.0001	-0.0019	0.0017	0.0006
	(-0.09)	(-1.24)	(1.36)	(0.65)
SIZE	-0.0017***	-0.0007	-0.0017***	-0.0012***
	(-3.18)	(-1.12)	(-4.06)	(-3.00)
LOSS	0.0198***	0.0157***	0.0150***	0.0117***
	(9.23)	(9.87)	(9.49)	(10.91)
ROAVOL	0.0434***	0.0316***	0.0379***	0.0269***
	(4.36)	(5.22)	(5.30)	(6.19)
LEV	0.0340***	0.0168***	0.0289***	0.0136***
	(6.44)	(3.68)	(7.73)	(4.51)
RD	-0.0001	0.0012	-0.0002	0.0002
	(-0.08)	(0.90)	(-0.23)	(0.23)
BM	0.0274***	0.0243***	0.0221***	0.0198***
	(10.68)	(9.37)	(12.04)	(10.59)
Constant	-0.0367***	-0.0286***	-0.0260***	-0.0136
	(-3.67)	(-3.18)	(-3.73)	(-1.47)
Controls	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Observations	13,842	14,563	13,842	14,563
Adj. R-squared	0.145	0.127	0.173	0.141

Table 4.7: Robustness Test: PSM Sample

This table reports the regression results of testing the effects of the disclosures of physical shocks related to climate change on analyst forecast errors and dispersion for the propensity score matched sample. $CCExposure^{Phy}$ is the percentage of bigrams capturing physical shocks related to climate change occurring in the transcripts of earnings conference calls (Sautner et al., 2023a). The Appendix provides the definitions of all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
	FERROR	*DISPERSION*
$CCExposure^{Phy}$	-0.0498**	-0.0203
	(-2.22)	(-1.24)
FHORIZON	0.0002***	0.0001***
	(4.20)	(3.75)
ANANO	-0.0005	0.0016
	(-0.19)	(0.86)
SIZE	-0.0010	-0.0013*
	(-1.06)	(-1.93)
LOSS	0.0192***	0.0132***
	(5.42)	(5.18)
ROAVOL	0.0473***	0.0350***
	(2.78)	(2.86)
LEV	0.0392***	0.0309***
	(4.17)	(5.04)
RD	0.0006	-0.0007
	(0.26)	(-0.40)
BM	0.0324***	0.0252***
	(6.40)	(7.04)
Constant	-0.0527***	-0.0338***
	(-4.06)	(-3.87)
Year fixed effects	yes	yes
Industry fixed effects	yes	yes
Observations	4,052	4,052
Adj. R-squared	0.159	0.185

Table 4.8: Robustness Test: Sample Firms Followed by at Least Two Analysts

This table reports the regression results of testing the effects of the disclosures of physical shocks related to climate change on analyst forecast errors and dispersion for the expanded sample that include firms followed by at least two analysts. $CCExposure^{Phy}$ is the percentage of bigrams capturing physical shocks related to climate change occurring in the transcripts of earnings conference calls (Sautner et al., 2023a). The Appendix provides the definitions of all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
	FERROR	*DISPERSION*
$CCExposure^{Phy}$	-0.0360**	-0.0174
	(-2.22)	(-1.33)
FHORIZON	0.0002***	0.0001***
	(12.10)	(11.24)
ANANO	-0.0010	0.0018**
	(-0.93)	(2.45)
SIZE	-0.0012***	-0.0015***
	(-3.05)	(-5.18)
LOSS	0.0173***	0.0129***
	(14.09)	(14.75)
ROAVOL	0.0405***	0.0357***
	(7.90)	(9.17)
LEV	0.0261***	0.0220***
	(7.91)	(9.44)
RD	0.0002	-0.0001
	(0.20)	(-0.19)
BM	0.0278***	0.0226***
	(15.61)	(17.77)
Constant	-0.0382***	-0.0255***
	(-5.88)	(-4.76)
Year fixed effects	yes	yes
Industry fixed effects	yes	yes
Observations	32,617	32,617
Adj. R-squared	0.146	0.166

Table 4.9: Robustness Test: Adding COVID Period

This table reports the regression results of testing the effects of disclosures of physical shocks related to climate change on analyst forecast errors and dispersion for the extended sample period from 2002 to 2020 (including the COVID period). $CCExposure^{Phy}$ is the percentage of bigrams capturing physical shocks related to climate change occurring in the transcripts of earnings conference calls (Sautner et al., 2022a). The Appendix provides the definitions of all the variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
	FERROR	*DISPERSION*
$CCExposure^{Phy}$	-0.0331*	-0.0110
	(-1.76)	(-0.69)
FHORIZON	0.0002***	0.0001***
	(11.81)	(10.74)
ANANO	-0.0010	0.0014*
	(-0.92)	(1.79)
SIZE	-0.0012***	-0.0014***
	(-3.15)	(-5.08)
LOSS	0.0157***	0.0123***
	(13.74)	(14.79)
ROAVOL	0.0389***	0.0328***
	(8.05)	(9.28)
LEV	0.0246***	0.0207***
	(8.02)	(9.43)
RD	-0.0004	-0.0008
	(-0.37)	(-1.12)
BM	0.0268***	0.0223***
	(15.61)	(17.87)
Constant	-0.0352***	-0.0234***
	(-5.97)	(-4.77)
Year fixed effects	yes	yes
Industry fixed effects	yes	yes
Observations	32,946	32,946
Adj. R-squared	0.147	0.168

Table 4.10: Robustness Test: Controlling for Physical Risk Disclosures in 10-Ks

This table reports the regression results of testing the effects of the disclosures of physical shocks related to climate change on analyst forecast errors and dispersion after controlling for physical risk disclosures in firms' 10-K reports. *CCExposure*^{Phy} is the percentage of bigrams capturing physical shocks related to climate change occurring in the transcripts of earnings conference calls (Sautner et al., 2022a). *Physical10K* is percentage of sentences related to physical risk in the Item 1.A of a firm's 10-K report (Kölbel et al., 2021). The Appendix provides the definitions of all other variables. The standard errors of the estimated coefficients are adjusted for firm-level clustering. The *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
	FERROR	*DISPERSION*
CCExposure^{Phy}	-0.0394**	-0.0171
	(-2.02)	(-1.09)
Physical10K	-0.0165	-0.0178
	(-1.08)	(-1.34)
FHORIZON	0.0002***	0.0001***
	(11.46)	(10.48)
ANANO	-0.0008	0.0015*
	(-0.75)	(1.79)
SIZE	-0.0011***	-0.0014***
	(-2.71)	(-4.59)
LOSS	0.0169***	0.0130***
	(13.55)	(14.45)
ROAVOL	0.0385***	0.0338***
	(7.51)	(8.88)
LEV	0.0246***	0.0209***
	(7.41)	(9.00)
RD	-0.0002	-0.0006
	(-0.23)	(-0.79)
BM	0.0279***	0.0230***
	(14.92)	(17.29)
Constant	-0.0375***	-0.0245***
	(-5.93)	(-4.61)
Year fixed effects	yes	yes
Industry fixed effects	yes	yes
Observations	31,006	31,006
Adj. R-squared	0.144	0.168