An Introduction to the Pricing of Climate Bonds via Machine Learning[1]

Romain Berrou[2,3]

Abstract

In this study, we attempt to determine if corporate bonds issued by climate-aligned firms are priced differently by corporate bond markets. Relying on trade-based data from the TRACE database to obtain the most indicative monthly prices on corporate bonds, we apply machine learning methods and attempt to predict future corporate bond returns by using a set of predictors taken or adapted from the bond pricing and stock pricing literature. We add a dummy variable that identifies climate bonds to see if our machine learning algorithms use this information to predict future bond returns. We find that the climate dummy variable is almost never used to price corporate bonds throughout hundreds of different model fits, indicating that to date, the fact that an issuer is climate-aligned is not taken under account by corporate bond markets to price corporate bonds.

Keywords: Machine Learning; Green Bonds; Sustainable Finance; Return Prediction; Cross-Section of Returns; Ridge Regression; Lasso; Elastic Net; Random Forest

---

[1] This study has been realised in the frame of the Chair Finagri of the University Paris 1 Panthéon-Sorbonne. The works of the Chair have benefitted the joint participation of the IAE (*Institut d'administration des entreprises*) as well as the participation of professionals from the financial industry. We thank all the participants to the works of the Chair for their precious contribution to the improvement of this paper.

[2] IAE Paris - Sorbonne

[3] The author can be reached via e-mail at romain.berrou@etu.univ-paris1.fr

1. Introduction

Data science and machine learning are changing the entire financial landscape, and machine learning methods and algorithms are increasingly viewed by academics in finance as the future of empirical financial research. In the first sentence of his very well received book on the subject, Marcos Lopez de Prado, one of the leading scholars on machine learning (ML) in finance, states that "today's machine learning (ML) algorithms have conquered the major strategy games, and are routinely used to execute tasks once only possible by a limited group of experts. Over the next few years, ML algorithms will transform finance beyond anything we know today." Amongst the different comments on Lopez de Prado's work is that of Campbell Harvey, former President of the American Finance Association and leading scholar in the asset pricing literature, which reads: "The first wave of quantitative innovation in finance was led by Markowitz optimization. Machine learning is the second wave, and it will touch every aspect of finance" further stating that Lopez de Prado's work on the subject is "essential for readers who want to be ahead of the technology rather than being replaced by it." (Lopez de Prado, 2018).

As we will see in the following section, machine learning methods are slowly making their way into the stock pricing literature. To date, however, these methods have not been used in the context of the corporate bond pricing literature, which is a more recent and less developed. This is mostly due to the fact that historically, obtaining reliable corporate bond prices has been much more complex[4]. In addition, data on corporate bond prices is generally either matrix-based or quote-based instead of purely transaction-based, and therefore less reliable. Fortunately, the Trade Reporting and Compliance Engine (TRACE) database opened in 2002, providing academics with purely trade-based data on the US corporate bond market and leading to the first studies on corporate bond asset pricing. In the context of this study, we rely mainly on Bai, Bali and Wen (2019) to construct our bond-specific predictors. In their study, the authors use TRACE data to construct their monthly prices and put forward a model based on four predictors that best explains the cross-section of US corporate bond returns. We include these predictors and include or adapt all the control variables that were used in their study to test the robustness of their results in our set of predictors.

Finally, we rely on Gu, Kelly and Xiu (2020) to construct our methodology and include some predictors adapted from the stock literature in our models. In this study, the authors provide a comparison of the main machine learning methods that are available for academics that wish to better understand and predict future stock returns. We adapt this methodology as well as some stock-based predictors to our study of corporate bond pricing.

We run our different machine learning methods on a sample of 1,279,861 bond-month return observations for 40,657 US corporate bonds over the 165-month period going from June 2005 to February 2019. We first run our models using a set of 23 predictors without including the climate dummy variable, in order to understand the impact of adding the climate predictor to our models in a second step. All our predictors are determined on a monthly basis, and we separate our dataset in a

[4] Data on corporate bond prices has almost entirely disappeared between 1997 and 2004 as the Lehman Brothers Fixed Income Database closed in December 1997 and the Mergent Fixed Income Securities Database (FISD) opened in 2004.

training sample of 60 months, a validation sample of 20 months, and 85 months of monthly test samples. We apply a cross-validation technique that respects the temporal structure of our data.

When the climate variable is excluded from our predictors, only one machine learning method – the Principal Component Regression (PCR) method - succeeds in obtaining a positive average out-of-sample R-squared over the 85 monthly-test samples. Throughout the different machine learning methods that can select the best performing predictors[5], the most impactful predictor is a bond's time to maturity, followed by its beta with the profitability factor. Along with the bond's beta with the stock market risk factor, three of the four factors developed in Bai, Bali and Wen (2019) are in the six most impactful predictors for our models. However, these predictors do not suffice for our models to constantly obtain positive out-of-sample R-squared throughout our 85 test-month samples.

Overall, adding a climate variable worsens our results, slightly improving our worst performing traditional linear methods and worsening our best performing machine learning models. With the climate dummy variable included, none of our machine learning methods succeed in obtaining a positive average out-of-sample R-squared over the 85 monthly-test samples. Our analysis of variable importance throughout the machine learning models provide us with interesting insight: the climate bond variable is barely used at all by any of our machine learning methods throughout hundreds of different model fits. The results of this study lead us to conclude that the fact that an issuer is climate-aligned is not taken under account by corporate bond markets to price corporate bonds.

2. Literature Review

In this work, we follow the definition of "machine learning" provided by Gu, Kelly and Xiu (2020). In their study on machine learning in asset pricing, the authors define the term as "(a) a diverse collection of high-dimensional models for statistical prediction, combined with (b) so-called "regularization" methods for model selection and mitigation of overfit, and (c) efficient algorithms for searching among a vast number of potential model specifications". The high-dimensional aspect of ML methods provides more flexibility compared to more traditional econometric methods and allows for better approximation of risk premiums. This however comes at a price of higher risk of overfit, which, as we will see in this section, represents a central subject today in the field of asset pricing. To minimize the risks of overfit, ML techniques include tools specifically designed to enhance out-of-sample performance. The final challenge that can be resolved with ML methods consists in finding the optimal model permutations when dealing with a high number of variables, a challenge that was also central to the asset pricing literature which had relied on logic to put forward the potential predictors it though were most likely to impact the cross-section of stock returns.

Within the financial literature, machine learning methods have mostly emerged in the context of the asset pricing research. A lasso regression[6] method was applied to predict international stock returns and understand the role of the United States in these global market returns (Rapach, Jack, Strauss and Zhou, 2013). Regression trees were used to predict credit card risk (Butaru, Florentin, Chen, Clark, Das, Lo

[5] These are the machine learning technique that allow for variable selection and dimension reduction techniques such as Elastic Net, Principal Component Regression and Partial Least Square.

[6] Lasso (least absolute shrinkage and selection operator) regression is a machine learning method that consists in performing both variable selection and regularization to optimize the accuracy and interpretability of the produced statistical model.

and Siddique, 2016) and model consumer credit-risk (Khandani, Amir, Kim, Lo, 2010). Neural networks have been used to price and hedge derivatives (Hutchinson, James, Lo and Poggio, 1994), model mortgage prepayment and delinquencies (Sirignano, Justin, Sadhwani and Giesecke, 2016), and to perform portfolio selection (Heaton, Polson and Witte, 2017).

Focusing more precisely on the cross-section of expected returns, several technical reports for the University of Chicago and Duke University have applied machine learning techniques to improve their regression models. These include using the bootstrap procedure (Harvey and Liu, 2019) as well as dimension reduction methods for factor pricing models (Giglio and Xiu, 2017; Kelly, Pruitt and Su, 2017). Tree-based models have also been used to sort portfolios in order to establish a relationship between past and future stock returns (Moritz and Zimmermann, 2016). Other reports from the University of Michigan (Kozak, Nagel and Santosh, 2017) and the University of Wisconsin-Madison (Freyberger, Neuhierl and Weber, 2017) have worked on applying selection methods and shrinkage in the context of the study of the cross-section of expected returns.

Looking at the machine learning literature, many authors have realized that machine learning methods could be applied to the consequential challenge of using times series data to predict stock market returns, and that their models could be used to develop profitable strategies regardless of the efficient market hypothesis (Henrique, Sobreiro, Kimura, 2019). The efficient market hypothesis was developed by Malkiel and Fama (1970) but was revised more than 20 years later by Fama (1991) when the author established that financial markets followed random directions and were therefore unpredictable. More recently, the efficiency of financial markets has been challenged many times, and authors both from machine learning research (Atsalakis and Valavanis, 2009) and finance research (Malkiel, 2003) have addressed this issue by summarizing different works in their field. Given the non-stationary, non-linearity, noisy and chaotic nature of price time series in financial markets, and the fact that these can be influenced by a variety of economic, financial, political or even psychological factors, research on the subject has generated much interest in the machine learning community (Henrique, Sobreiro, Kimura, 2019). Prediction models developed by the machine learning academic community are applied to financial distress estimation (Chen and Du, 2009) and stock trading prediction (Chang, Liu, Lin, Fan and Ng, 2009; de Oliveira, Nobre, and Zarate, 2013), with a series of studies successfully identifying profitable opportunities (Doeksen, Abraham, Thomas, and Paprzycki, 2005; Huang, Yang and Chuang, 2008; Patel, Shah, Thakkar and Kotecha, 2015).

To date, there are few studies that focus on applying machine learning methods to bond markets. Bianchi, Buchner and Tamoni (2019) apply such methods to estimate bond risk premia following the work on equity risk premia by Gu, Kelly and Xiu (2019) on Treasury Bond data. Other studies focus on more specific technical subjects, such as using machine learning to identify clients that are most likely to be interested in a given bond (Wright, Capriotti, Lee, 2018), or to improve the quality of corporate bond yield data (Kirczenow, Hashemi, Fathi and Davison, 2018). Given the positive results of machine learning on market price prediction both for equity and treasury bond markets, it seems clear that machine learning methods will increasingly be used in financial research.

3. Data

3.1. Required databases for corporate bond and climate bond pricing

For this paper, we use three distinct sources of data. We obtain transaction data for the US corporate bond market through the TRACE database, which we use to compute corporate bond returns. We use the FISD database to obtain information on bond characteristics. Finally, we obtain a list of climate bond issuers from the Climate Bond Initiative, which we use to identify climate bonds through the FISD database.

Since June 2002, all corporate bond transactions in the secondary market have been made available with the TRACE system through the Trade Reporting Compliance Engine[7]. Before this new dataset was made available, most studies that focused on the corporate bond market only used daily quotes and matrix prices for corporate bonds, which could bias results. In their paper on the subject, Sarig and Warga (1989) explore the fact that there can be liquidity-driven noise errors in daily prices for corporate bonds since daily prices are given even on days when bonds have not been traded for multiple days. When this is the case, brokers set matrix prices based on similar bonds issued by issuers with similar characteristics, which creates bias. More recently, Dick-Nielsen (2009) shows that this bias still exists with prices from Datastream[8]. This gives TRACE data a considerable edge when focusing on daily prices that can be used for microstructure research such as event studies, as well as an edge for weekly and monthly prices.

Two distinct versions of TRACE exist: the standard TRACE data that censors trading volumes that are greater than $5 million for investment grade bonds and greater than $1 million for speculative grade bonds and that usually has a three-month lag for the availability of data, and the enhanced TRACE data, that has information on all transaction volumes but has an 18 month lag for the availability of data. In this paper, we refer to enhanced TRACE data, which spans from June 2002 to March 31st 2019.

Considering bond characteristic, FISD is considered as the most comprehensive database focusing on bonds and contains detailed information on the characteristics of more than 140,000 US bonds, either corporate bonds, supranational bonds, U.S. Agency Bonds and U.S. Treasury Bonds. The FISD database contains essential information on bond issuers as well as specific bond issues such as bond issue date, maturity, size, coupon, type, and any information that can be used to identify and categorize US bonds.

Finally, we use a list of climate bond issuers provided directly by the Climate Bond Initiative (CBI) research team. This list was used by CBI in their study on the climate bond market (Climate Bond Initiative, 2018). To identify climate bonds, CBI identified issuers that originated at least 75% of their revenues from green business lines in either clean energy, low-carbon buildings and transport, water and waste management and sustainable land use. Climate bonds were included if they were issued after the 1st of January 2005 and before the end of Q2 2018. Therefore, we use the list of issuers provided by the Climate Bond Initiative to identify all climate bond transactions available on the Enhanced

[7] The Trade Reporting and Compliance Engine (TRACE) was developed by the National Association of Securities Dealers (NASD) and is used for over-the-counter (OTC) transactions for fixed-income securities. This trade-based data is made available to academics through the TRACE database.

[8] As it is explained in Jostova, Nikolova, Philipov, Stahel (2013): "Extensive discussions with the DataStream support team about the source of their data confirmed that most U.S. corporate bond prices are dealer quotes reported by market-makers. These data are further augmented with trading prices for traded bonds. Like Lehman, DataStream provides no indication of whether a price is based on a quote or a trade."

TRACE database since June 2002 to the 31st of March 2019. Our database for traditional bonds uses all available Enhanced TRACE data on the same period.

3.2. From raw intraday transaction data to monthly corporate bond returns

As I continue to follow Bai, Bali and Wen (2019), I remove bonds that are not traded in in the US public market, bonds that are structured notes, mortgage or asset-backed, agency backed or equity-linked, convertible bonds, bonds with floating coupon rates, bonds that trade below \$5 or above \$1000 as well as bonds that have less than one year to maturity. Regarding transaction data, much like Bai, Bali and Wen, I remove bond transactions that are labeled as "when issued", "locked-in", that have special sales conditions and that have more than a two-day settlement. Furthermore, I also remove transactions that have a volume inferior to \$10,000. Finally, I follow the filtering methodology developed in Dick-Nielsen (2014) to remove cancellations and corrections made on the TRACE Enhanced database, as well as inter-dealer transactions that are reported twice in the trace database. Much like the author, I apply the two distinct approaches for pre- and post-2012 Enhanced TRACE data. After applying these different filters, my dataset is composed of 91,294,517 intraday transactions spanning from June 2002 to March 2019.

Once we obtain this intra-day information on bond transactions, we compute a daily price by referring to the "trade-weighted price, all trades" approach of Bessembinder et al. (2008), which consists in performing a value-weighted average of all intraday transaction prices. This methodology puts more emphasis on trades from institutional investors that benefit from lower execution costs, therefore providing a better accuracy for daily prices. Once we apply this methodology, our daily price dataset consists of 13,770,971 daily prices[9].

In order to obtain monthly prices from daily prices, I develop a methodology similar to that of Bai, Bali and Wen (2019). I first identify the bond price for the last trading day for each bond-month. If the last trading day is one of the last five trading days within month *t*, then this daily price is used as a monthly price. If that is not the case, I identify the bond price for the first trading day of month *t+1*. If this trading day is one of the first five trading days of month t+1, it is used as a price for month *t*. This allows for a more complete dataset of bond monthly prices in order to be able to compute more monthly returns using data from months *t* and *t+1*, where returns are either computed using (1) end of month *t-1* to end of month *t* daily prices (2) start of month *t* to end of month *t* daily prices (3) start of month *t* to start of month *t+1*. Using the methodology, we compute 1,761,543 monthly prices for our dataset.

The monthly corporate bond return at time t is computed as:

$$r_{i,t} = \frac{(P_{i,t} + AI_{i,t} + Coupon_{i,t}) - (P_{i,t-1} + AI_{i,t-1})}{P_{i,t-1} + AI_{i,t-1}}$$

9 In Bessembinder et al (2009), four distinct strategies are used to compute daily prices from TRACE data: using the last price reported in TRACE for the day ("last price, all trades"), construct daily prices by weighing each trade by size ("trade-weighted price, all trades"), eliminating all trades below \$100,000 dollars and using the last available price of the day ("last price, trade ≥ 100k"), and eliminating all trades below \$100,000 and weighing each trade by size ("trade-weighted price, trade ≥ 100k"). Even though we do apply a "trade-weighted price, all trades" in this paper, we do exclude trades below \$10,000 from our sample following Bai, Bali and Wen (2019).

where $P_{i,t}$ is the transaction price, $AI_{i,t}$ is accrued interest, and $Coupon_{i,t}$ is the coupon payment, if there is any, of bond i for month t. We obtain the necessary information to compute corporate bond returns from the FISD database.[10] In order to compute our returns, month prices need to be available for adjacent months. Our final dataset is composed of 1,530,745 corporate bond returns.

4. Variables

In order to select and compute our variables, we follow Gu, Kelly and Xiu (2018). In their study, the authors apply a series of machine learning methods to a sample of 30,000 individual stocks from 1957 to 2016 in order to predict stock market returns. Out of the 900 possible factors that are used to run these models and predict stock market returns, the authors find that the most successful types of factors are - in order from most informative to least informative - price trends factors, liquidity factors and volatility factors. Price trends factors include either stock or industry momentum and short-term reversals. Liquidity predictors include market value, dollar volume and bid-ask spreads. Finally, predictors linked to volatility include return volatility, idiosyncratic volatility, market beta or beta squared.

Going into more detail concerning the predictive power of each predictor, the authors provide a list illustrating the importance of each characteristic for each machine learning model they apply to their sample, which in turn provides a precise ranking of the impact of each individual variable in predicting stock market return. Furthermore, citations of the papers that first developed each predictor are made available by the authors.

There are some important differences between the approach of Gu, Kelly and Xiu (2020) and the chosen approach for this study. First and foremost, this study focuses on predicting corporate bond market returns, and therefore predictors need to be adapted to the corporate bond market. Much like Gu, Kelly and Xiu (2020) refer to the asset pricing literature that focuses on stock markets, I refer here to corporate bond literature to develop the predictors in this study. Predictors are either directly taken from the corporate bond pricing literature or adapted to corporate bonds from the stock pricing literature. Another important difference resides in the fact that the author is limited in terms of computing power and cannot reasonably run complex machine learning models on such a large number of predictors. Regardless, given the insight provided by Gu, Kelly and Xiu (2020), we select the most important factors in terms of price trends, liquidity and volatility in their sample of factors and adapt them to the corporate bond market when possible. A second important difference between our approach and that of Gu, Kelly and Xiu (2020) is that in this study, we develop factors that are available on a monthly basis to develop models that focus on predicting next-month bond returns. This means that the factors used in Gu, Kelly and Xiu (2020) have to be determined monthly. This information is also provided by the authors.

10 This includes the coupon rate, the dated date marking the start of the interest period, as well as the interest frequency.

Supplementing these selected variables are some other factors that are either taken directly from Bai, Bali and Wen (2019), or adapted from the study. Through their research, Bai, Bali and Wen (2019) observed that the literature that focus on the cross-section of corporate bond returns relied on stock market factors, based on the rational that the stock and bond markets are integrated, since both bonds and stocks value similar underlying assets. Their work goes against this more traditional approach by focusing on risk factors that are specific to the bond market. In addition to these bond specific factors, the authors use a series of control variables in their studies to demonstrate the explanatory power of their factors. Amongst these are the most renown risk factors in the literature. These are the excess-stock market return (MKTstock), the size factor (SMB), the book-to-market factor (HML), the profitability factor (RMW), the investment factor (CMA), the momentum factor (MOM) and the liquidity risk factor (LIQ), which have been developed and computed in Fama and French (1993), Carhart (1997) and Pastor and Stambaugh (2003)[11]. These factors were developed at portfolio levels. Following Gu, Kelly and Xiu (2018), I apply machine learning methods in this study that can be applied at bond-level and do not need to use control variables at a portfolio level. Much like it is performed in Bai, Bali and Wen (2019), I create bond-level factors by computing betas for each of these portfolio-level factors. In the following subsections we explore four categories of factors in accordance with the results of Gu, Kelly and Xiu (2018): price-trend factors, volatility factors, liquidity factors, and a subsection addressing other types factors we have chosen to take under consideration. The last subsection explores the summary statistics of our dataset. In Table 1, we summarize our selected factors, provide the reference of the original paper and a description of how we compute the predictor with our data. Information on whether the factor is monthly or yearly is also provided.

4.1. Price-trend factors

Price trends taken from the stock asset pricing literature that focus on monthly returns are relatively straightforward to adapt to the corporate bond market, since the processes that need to be performed are similar and only require monthly corporate bond returns. Most of the price-trend factors Gu, Kelly and Xiu (2020) are momentum factors. However, some factors rely on accounting data that is only available on a yearly basis and cannot be used in this study. Some examples of these include the sales to price ratio factor (sp), the number of earnings increases factor (nincr) and the earnings to price factor (ep). Momentum factors we include in our study are the 1-month (mom1m), 6-month (mom6m), 12-month (mom12m) and 36-month (mom36m) momentum factors, each corresponding to the sum of returns in the period previous to month-t, with 1-month momentum corresponding to monthly returns in months t-1. The original 12-month momentum factor was discovered by Jegadeesh (1990), and the 1-month,6-month and 36-month momentum factors were developed in Jegadeesh and Titman (1993). Other momentum factors include the industry momentum factor, which was developed by Moskowitz and

11 Much like the risk-free rate, the excess-stock market return (MKTstock), the size factor (SMB), the book-to-market factor (HML), the profitability factor (RMW), the investment factor (CMA), the momentum factor (MOM) and the liquidity risk factor (LIQ) can be found online, either on Kenneth French's website https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ or Lubos Pastor's website https://faculty.chicagobooth.edu/lubos-pastor/research

Grinblatt (1999) and consists in computing 6-month momentums for industry portfolios, and the momentum change factor, which consists in computing the difference between 6-month momentum and momentum between month t – 12 and momentum between month t – 6 (Gettleman and Marks, 2006).

The last price trend factor that we choose to adapt from Gu, Kelly and Xiu (2020) is the maximum daily return factor, and consists, like its name indicates, in finding the maximum daily return for every month. In order to compute this predictor, we use our dataset of daily prices computed from TRACE and determine daily returns using these daily prices. The original max daily return was developed by Bali, Cakici & Whitelaw (2011).

Finally, I include the Value-at-risk (VaR) factor in our sample of factors. VaR measures the proportion by which the price of an asset could decline over a certain period of time as a result of variations in market rates or prices. To develop our measure for VaR we follow Bai, Bali and Wen (2020) a create a proxy by selecting the second lowest monthly return in a 36-month period prior to month t. Our measure is then multiplied by -1 in order to have positive values for VaR.

4.2. Liquidity factors

The liquidity measure that we use in this study is that developed by Bao, Pan and Wang (2011), which is also used in the study on the cross-section of corporate bond returns by Bai, Bali and Wen (2019).

The authors define P_t as a bond's clean price (meaning the price of a bond without accounting for accrued interests and coupon payment) at time t and p_t as the log price, and assume that p_t consists of the following components :

$$p_t = f_t + u_t$$

Where f_t represents the fundamental value of the log price in the absence of friction, and u_t is generated from the impact of illiquidity. Therefore, in the author's framework, u_t characterizes illiquidity on the market.

Finally, the authors define their measure for illiquidity, which is aimed at extracting this component in the observed clean log price, as follows:

$$\gamma = -Cov(\Delta p_t, \Delta p_{t+1})$$

With $\Delta p_t = p_t - p_{t-1}$. Bao et al. (2011) develop this model under the assumption that follows a random walk, so that γ only depends on u_t and therefore increases when u_t increases.

4.3. Volatility factors

Our selected volatility factors include the bond market beta developed by Bai, Bali and Wen (2019) and the tradition stock market beta from Fama-French (1993). Following the authors, we first determine bond market excess return by computing value-weighted average returns of all corporate bonds in our sample and subtract the one-month treasury bill rate from these values, and then perform a time-series regression of every bond's excess returns on the bond market excess return using a 36-months rolling-window. In order to compute the stock market beta, we export the stock market excess return (*Mkt-Rf*) from Kenneth French's website and perform the same operation with each corporate bond's excess monthly returns.

4.4. Other factors

Other factors are included in this study that are not considered price trends, liquidity or volatility factors. This includes the credit quality factor from Bai, Bali and Wen (2019), which consists in computing the monthly average of S&P, Moody's and Fitch ratings for every bond. In addition, I also include the two bond-level control variables that are used by the authors: bond maturity, which corresponds to the number of years left at month t before bond reaches maturity, and bond size, which corresponds to the amount outstanding of the bond.

Finally, I include several factors that consist in computing the betas of several renown bond-level factors that are used in the literature and by Bai, Bali and Wen (2019) as control variables. These are the betas of the aforementioned stock market return (MKTstock), size factor (SMB), book-to-market factor (HML), profitability factor (RMW), investment factor (CMA), momentum factor (MOM) and liquidity risk factor (LIQ) developed and computed in Fama and French (1993), Carhart (1997) and Pastor and Stambaugh (2003). We compute betas by performing time-series regressions of individual bond excess returns on each risk factor using a 36-month rolling-window.

5. Methodology

Throughout this paper, we follow the methodology developed in Gu, Kelly and Xiu (2020). In their work, the authors compare the performance of different ML methods in predicting stock returns. This includes (1) linear models, including the traditional ordinary least squares (OLS); (2) generalized linear models that apply penalization methods such as elastic net, LASSO[12] and ridge regressions; (3) methods that apply dimension reduction techniques such as principal component regressions and partial least squares; (4) regressions trees and (5) neural networks.

For each type of model, Gu, Kelly and Xiu (2020) provide a statistical model describing how the method is adapted to risk premium predictions, an objective function to estimates the parameters of the model and the computational algorithms corresponding to the model. The authors' objective for each model is to minimize the mean square predictions error (MSE). In the context of this study, the authors describe an asset's excess return as an additive prediction error model:

$$r_{i,t+1} = \mathrm{E}_t\left(r_{i,t+1}\right) + \epsilon_{i,t+1}$$

where

$$\mathrm{E}_t(r_{i,t+1}) = g^{\star}\left(z_{i,t}\right)$$

And stocks are indexed as i = 1, …, Nt and months by t = 1, …, T. With this approach, the authors attempt to isolate $\mathrm{E}_t(r_{i,t+1})$ as a function of variables that maximizes the out-of-sample explanatory power for $r_{i,t+1}$. $z_{i,t}$ represents the P-dimensional vector of variables and $g^{\star}(\cdot)$ is a flexible function of these variables.

---

[12] LASSO stands for least absolute shrinkage and selection operator

Table 1

Acronym	Predictor	Reference	Type of predictor	Computation
From Gu, Kelly and Xiu (2020)				
mom1m	1-month momentum	Jegadeesh & Titman (1993)	Price-trend	Return in month t-1
mom12m	12-month momentum	Jegadeesh (1981)	Price-trend	Cumulative returns between month t-12 and t-1
chmom	Change in 6-month momentum	Gettleman & Marks (2006)	Price-trend	Cumulative returns between month t-6 and t-1 minus by Cumulative returns between month t-12 and t-6
maxret	Maximum daily return	Bali, Cakici & Whitelaw (2011)	Price-trend	Maximum daily return of month t-1
indmom	Industry momentum	Moskowitz & Grinblatt (1999)	Price-trend	Cumulative returns of industry portfolio between t-6 and t-1
dolvol	Dollar trading volume	Chordia, Subrahmanyam & Anshuman (2001)	Liquidity	The natural logarithm of the dollar volume of trading in the security in month t-2
mom6m	6-month momentum	Jegadeesh & Titman (1993)	Price-trend	Cumulative returns between month t-6 and t-1
mom36m	36-month momentum	Jegadeesh & Titman (1993)	Price-trend	Cumulative returns between month t-36 and t-1
ill	Amihud liquidity measure	Amihud (2002)	Liquidity	Sum of absolute daily returns divided by daily dollar volume over each month
From Bai, Bali and Wen (2019)				
- Main predictors				
VaR	5% Value at risk	Bai, Bali and Wen (2019)	Price trend	Second lowest monthly return observation over the past 36 months
meangrade	Credit Quality	Bai, Bali and Wen (adapted from)	Other	Average monthly rating between S&P Ratings, Moody's Ratings and Fitch Ratings
Illiq	Bond Illiquidity	Bai, Bali and Wen (2019)	Liquidity	Bao liqiudity measure
βbond	Bond Market Beta	Bai, Bali and Wen (2019)	Volatility	Time-series regressions of individual bond excess returns on the bond market excess returns using a 36-month rolling window
- Control Variables				
timetomat	Time to maturity of the bond	Bai, Bali and Wen (2019)	Other	Number of years left until bond reaches maturity
Size	Bond size	Bai, Bali and Wen (2019)	Other	Amount outstanding of the bond at month t - 1
β DEF	Default Beta	Fama and French (1993) (adapted from)	Volatility/Other	Time-series regressions of individual bond excess returns on the Fama-French default factor using a 36-month rolling window
β TERM	Term Beta	Fama and French (1993) (adapted from)	Volatility/Other	Time-series regressions of individual bond excess returns on the Fama-French term factor using a 36-month rolling window
β Mkt-Rf	Stock Market Risk Beta	Fama and French (1993) (adapted from)	Volatility	Time-series regressions of individual bond excess returns on the Fama-French stock market risk factor using a 36-month rolling window
β SMB	Size Beta	Fama and French (1993) (adapted from)	Volatility/Other	Time-series regressions of individual bond excess returns on the Fama-French size factor using a 36-month rolling window
β HML	Value Beta	Fama and French (1993) (adapted from)	Volatility/Other	Time-series regressions of individual bond excess returns on the Fama-French book-to-market factor using a 36-month rolling window
β MOM	Momentum Beta	Carhart (1997) (adapted from)	Volatility/Price Trend	Time-series regressions of individual bond excess returns on the Carhart momentum factor using a 36-month rolling window
β LIQ	Liquidity Beta	Pastor and Stambaugh (2003) (adapted from)	Volatility/Liquidity	Time-series regressions of individual bond excess returns on the Pastor and Stambaugh liquidity measure using a 36-month rolling window

This approach does have important limitations. $g^{\star}(\cdot)$ does not depend on i or t. Contrarily to standard asset pricing approaches that reestimate a time-series model for each asset or a cross-section model for each time-period, this model maintains the same form through time and across assets, providing more stability with regards to the risk premium estimates of assets. Furthermore, $g^{\star}(\cdot)$ depends only on z through $z_{i,t}$, meaning the model's predictions do not use any information from historical data prior to t or any other asset than the ith.

As we continue to follow the methodology of Gu, Kelly and Xiu (2020) every model description in this study can be found in the authors' work, with the following exceptions: our linear models rely on a standard least squares objective function without its robust extension and we perform our generalized linear model without performing a group lasso[13].

5.1. Sample splitting and tuning via cross-validation

The application of ML methods requires preforming specific preliminary steps. In order to be able to perform regularization - the central tool applied in the context of ML methods to minimize overfitting - a choice regarding hyperparameters needs to be made. Hyperparameters control the complexity of models, and for each ML method applied to data, a choice of hyperparameter14 will lead to the best possible result from the model in out-of-sample data. In order to determine the best value for a model's hyperparameter, the data sample is divided in three different time periods maintaining similar temporal ordering. The first sample, the "training" sample, is used to estimate the model that will be subject the hyperparameters. The second sample, the "validation" sample, is used to determine the optimal value for the hyperparameter. In order to do that, forecasted datapoints are determined in the validation sample using the model applied to the training sample, and the optimal hyperparameter is found iteratively based on forecasts errors in the validation set. It is important to note here that the model used in the training data needs to be re-estimated every time a new hyperparameter is tested. The idea of the validation sub-sample is to stimulate a form of out-of-sample test of the model and find the hyperparameter values that correspond to the optimal level of complexity of the model that produces the best results in the validation sample. Once the optimal model, hyperparameter and model complexity have been determined, the "testing" subsample, which is truly out-of-sample because it has not been used for either estimation or tuning, is used to evaluate the out-of-sample predictive performance of a method.

There are a few differences between this paper and Gu, Kelly and Xiu (2020) that we can benefit from, and which impact our approach to sample splitting and tuning via validation. First and foremost, in the context of this paper, we are more limited in terms of computational power, and therefore limit the ML methods we apply to the less computationally intensive. The methods we apply throughout this paper are linear-based : they are the standard ordinary least square (OLS) method, using either the four factor of Bai, Bali and Wen (2020) or the our entire set of factors, the Elastic Net method, the Principal

[13] In Gu, Kelly and Xiu (2020), the linear model description is performed in section 1.2, the description of the statistical model for the elastic net is performed in section 1.3, PCR and PLS methods are described in section 1.4 and the generalized linear model is explained in section 1.5.

[14] Main examples of hyperparameters include penalization parameters for elastic net, the number of trees in boosting or the number of random trees in a forest

Component Regression (PCR), the Partial Least Square (PLS) method and the Generalized Linear Model (GLM) method, which we define in the following sub-sections.

Furthermore, the period we study for our sample is smaller than that of Gu, Kelly and Xiu (2020). The authors study stock prices from 1956 to 2016 when our sample spans from 2005 to 2019. This provides with another opportunity which consists in fitting out models monthly instead of yearly. This is even more interesting because our variables are computed monthly and therefore provide new monthly information that can be used by our different models.

The last central difference between our study and Gu, Kelly and Xiu (2020) consists in the fact that we apply a cross-validation technique that maintains the temporal ordering of our data. Given the fact that some of our variables require 36 months of previous monthly data to be computed, and that data from TRACE is first made available in June 2002, our models run on data from June 2005 to March 2019. Our approach then consists in the following steps:

- We use a 5 years / 60 months period for our training sample.
- We require 20 further months for our validation sample.
- We test our models on the month following the last month of the validation sample

Each month in our validation sample is used to fit a model using a different hyperparameter. This gives our ML methods 20 different samples to try to fit the best possible model. Every time a month in our validation sample is used to fit a model using a new hyperparameter, we then integrate this month in our training sample while maintaining a training sample of 60 months. We then use the following month as our validation sample. This method allows us to perform cross-validation while maintaining the temporal ordering of the data. Since our dataset starts on June 2005 and we maintain a 60-month training sample and a 20 months validation sample, our first test month is on March 2012. We therefore have 7 years (84 months) of different test results for our different models. We explore these results in the following section.

6. Results

6.1. Models without Climate dummy variables

We test each of our machine learning methods for every month from March 2012 to February 2019. Our results vary between months and ML methods and are summarized in Table 2. The full extent of the different obtained out-of-sample R-squared are available in Appendix 1. Monthly out-of-sample R-squared are represented in Figure 1.

Table 2

Month	OLS4 - R*oos*	OLS - R*oos*	Elastic Net - R*oos*	PCR - R*oos*	PLS - R*oos*	Glm - R*oos*
Min	-0.517	-0.782	-0.187	-0.110	-0.130	-0.189
Median	-0.009	-0.065	-0.001	-0.001	-0.004	-0.065
Mean	-0.017	-0.085	-0.003	0.003	-0.003	-0.085
Max	0.290	0.419	0.164	0.087	0.093	0.419
Standard Deviation	0.097	0.134	0.064	0.032	0.065	0.134

Our results demonstrate that our models are unable to constantly obtain positive out-of-sample R-squared using the developed predictors. Though all models obtain both negative mean and median values over the sample period, some perform better than others. Both traditional linear models that used all variables – the Ordinary Least Square approach and generalized linear model approach - have the worst performance, with a mean out-of-sample R-square of -8.5% and a medium out-of-sample R-squared of -6.5%. These models also have the highest standard deviation for their performance with standard deviation of 0.134 each.

The OLS4 model, which represents the Ordinary Least Square approach using only the four factors of Bai, Bali and Wen (2019), has a much better performance, with a mean out-of-sample R-squared of -1.7% and a median out-of-sample R-squared of -0.9%. Though Bai, Bali and Wen (2019) do argue that their four-factor model outperform all other models to explain the cross-section of corporate returns, it seems this is still not sufficient to create a model that performs positively in predicting next-month bond returns.

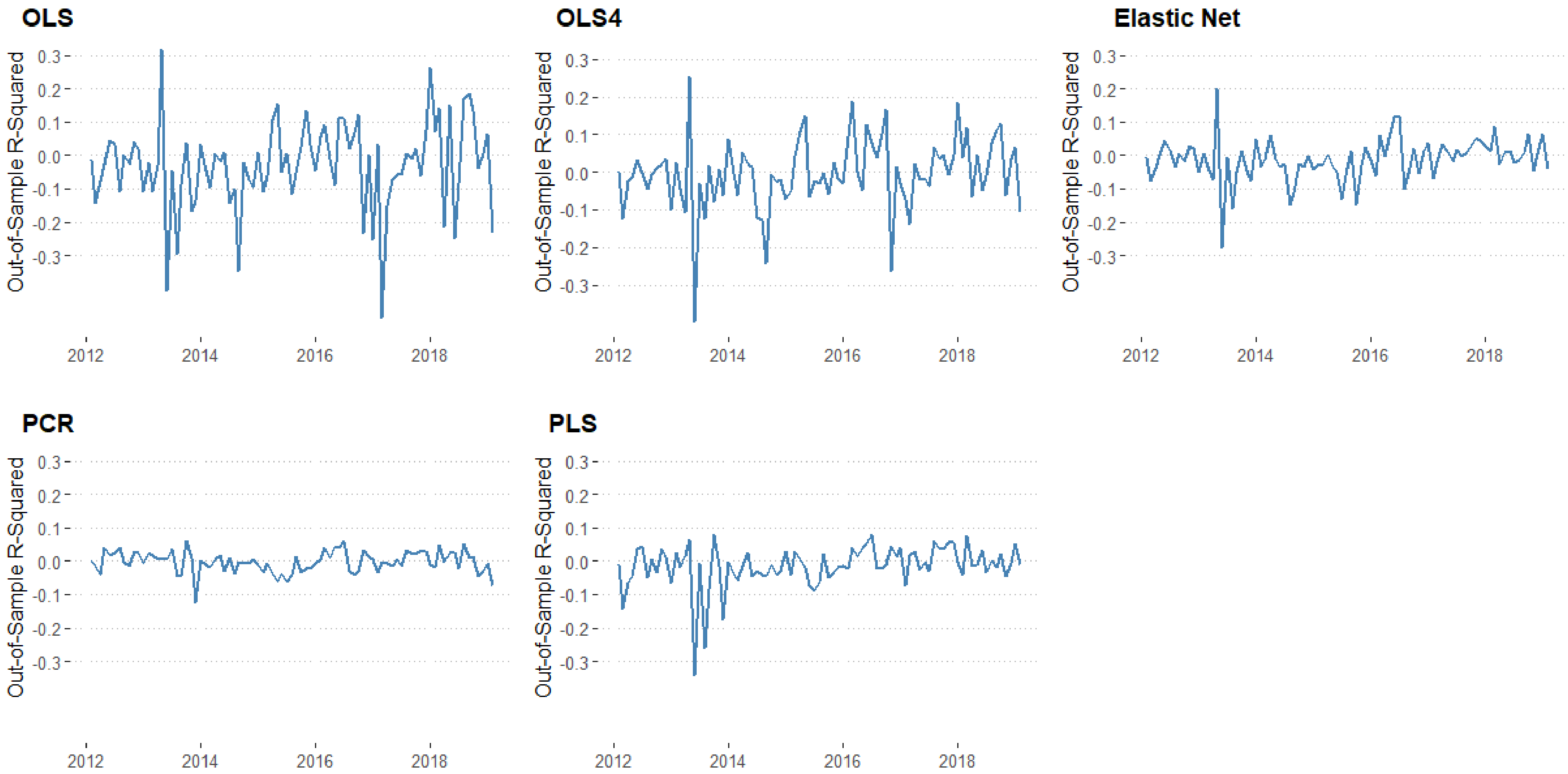
Finally, as it could be expected, ML methods that use shrinkage methods – such as the elastic net – and dimension reduction techniques – such as the principal component regression (PCR) or partial least square (PLS) method – perform better than standard linear models. The elastic net method has a mean out-of-sample R-Square of -0.3% and median out-of-sample R-squared of -0.1%, while the PLS approach has a similar mean out-of-sample R-Square of -0.3% and a slightly lower median out-of-sample R-squared of -0.4%. The PCR method is the only method to have positive mean out-of-sample R-squared of 0.3%, though median out-of-sample R-squared values are slightly in negative territory with -0.1%. The PCR method is also the one with the lowest standard deviation (0.032) compared to the other two methods (0.064 for elastic net and 0.065 for PLS). The fact that the PCR approach outperforms other approach could be explained by the fact that many of our price-trend variables are correlated and dimension reduction technique are best for dealing with correlated variables.

The volatility of monthly out-of-sample R-squared for each method can be visualized in Figure 1. Through these figures, we understand how each test-month showcases different performances for each type of method, and that some test months have quite high yet isolated out-of-sample R-squared. As an interesting example, we can observe that for the test month of May 2013, the standard OLS regression using every variable results in an out-of-sample R-squared of 30%, but then results in a very low out-of-sample R-squared of -40.6% for the next test-month of June 2013. From these representations, we can also notice how standard deviation differs between our models, with Elastic Net, PCR and PLS methods demonstrating much less variation and having out-of-sample R-squared performances varying at a much closer distance from 0.

6.2. Variable importance for models without climate dummy variable

While the traditional linear models that use none of the machine learning methods such as cross-validation, shrinkage or dimension reduction use all of the variables they are provided, Elastic Net, PCR and PLS machine learning methods use specific sets of predictors to obtain the best performing models. As previously mentioned, the Elastic Net method will in most cases use only a subset of provided predictors to create its best models and use the predictors they find to be the most impactful. Machine learning methods that use dimension reduction techniques perform a different type of operation and

Figure 1



OLS
OLS4
Elastic Net
PCR
PLS
Out-of-Sample R-Squared
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
2012
2014
2016
2018

learning methods that use dimension reduction techniques perform a different type of operation and construct new components that are composed of different predictors and use these constructed components as new variables for their models. Much like it is the case for the elastic net approach, both PCR and PLS methods use the most impactful predictors to construct these components. In table 2, we show the importance of each predictor in the construction of each methods' final model for every test month.

Table 3

Variables	Elastic Net	PCR	PLS	Mean
timetomat	0.362	1.000	1.000	0.787
betaRMW	0.550	0.376	0.893	0.606
meangrade	0.473	0.412	0.805	0.563
betaMktRF	0.154	0.418	0.974	0.515
VaR	0.212	0.343	0.751	0.435
MKTbond	1.000	0.000	0.304	0.435
betaMom	0.100	0.349	0.809	0.419
betaSMB	0.056	0.289	0.752	0.366
betaterm	0.032	0.325	0.609	0.322
betaHML	0.063	0.230	0.610	0.301
betadef	0.067	0.237	0.548	0.284
mom12m	0.332	0.142	0.314	0.263
maxday	0.317	0.106	0.361	0.261
realindmom	0.381	0.078	0.242	0.234
mom36m	0.113	0.146	0.367	0.209
ILLIQ	0.108	0.121	0.338	0.189
mom1m	0.395	0.029	0.114	0.180
betaCMA	0.073	0.109	0.299	0.160
size	0.040	0.194	0.171	0.135
momt6t1	0.018	0.125	0.220	0.121
betaAgg.Liq.	0.155	0.061	0.123	0.113
chmom	0.160	0.000	0.118	0.093
sd_turn	0.000	0.244	0.000	0.081

These results in terms of variable importance are insightful, both in the context of the work of Bai, Bali and Wen (2019) and of Gu, Kelly and Xiu (2020). In Bai, Bali and Wen (2019), the authors establish that the best model available to date to explain the cross-section of corporate bond returns is composed of 4 variables that they develop in their paper : the Value-at-risk variable (VaR) the credit rating variable (meangrade), and the illiquidity measure of Bao, Pan and Wang (2011) (ILLIQ) as well as the bond market risk (MKTbond). Table 2 confirms that throughout the hundreds of different model fits performed though these different machine learning methods, although three of these predictors are in the top six most important predictors overall, a bonds' time to maturity (timetomat) and a bond's beta with the profitability factor (betaRMW) are the most impactful predictors to determine next-month corporate bond returns. Interestingly, a bond's beta with the stock market risk factor (betaMktRF) is more important than its beta with the corporate bond market risk return (MKTBond).

Regarding Gu, Kelly and Xiu (2020), to date our linear machine learning models are unable to determine future corporate bond returns continually. Furthermore, it seems like predictors based on price trends have little role to play in determining future corporate bond returns compared to stock returns, as the first price trend predictor – twelve-month momentum (mom12m) – is only the twelfth most significant predictor for our different models. According to this study, and unlike Gu, Kellu and Xiu's (2020) on the stock market, the most impactful predictors in our sample are not the traditional price-trend, volatility and liquidity-based predictors but rather bond specific predictors such as time-to-maturity, credit rating, and betas with the literature's most important stock and bond-level risk factors.

It is also interesting to notice that for our elastic net models, the leading predictor is the bond market risk factor when our PCR models do not even use this predictor in constructing their models, which, in turn, seem slightly more efficient.

6.3. Models without Climate dummy variables

Once we have obtained our results, we run our models once again, this time integrating the climate dummy variable. This can help us understand whether or not the fact that a bond is issued by climate-aligned firms has an impact on its pricing and can be used by the machine to better approximate how the corporate bond's future price. Descriptive statistics of our new dataset are available in Table 4.

Table 4

Month	OLS4 - R*oos*	OLS - R*oos*	Elastic Net - R*oos*	PCR - R*oos*	PLS - R*oos*	Glm - R*oos*
Min	-0.397	-0.486	-0.277	-0.157	-0.345	-0.489
Median	-0.002	-0.022	-0.010	-0.003	-0.013	-0.023
Mean	-0.004	-0.030	-0.011	-0.004	-0.016	-0.030
Max	0.256	0.318	0.200	0.061	0.081	0.318
Standard Deviation	0.097	0.134	0.064	0.035	0.065	0.134

As we can see, adding a climate dummy variable changes some of our results. Interestingly, mean and median out-of-sample R-squared for our classic linear models are higher, when they are reduced for our Elastic Net, PCR and PLS methods. However, standard deviation for each method does not change. Overall, since our Elastic Net, PCR and PLS methods were providing us with the best results for our different predictors, adding a climate bond dummy does reduce our best mean out-of-sample R-squared from 0.3% from our PCR method to -0.4% from both our OLS4 approach and our PCR approach with climate dummy variable.

6.4. Models without Climate dummy variables

We perform a new variable importance analysis on the machine learning methods and models that include a climate dummy variable, and find that the climate variable is the least used variable for all three machine learning methods that are elastic net, PCR and PLS. This means that even though hundreds of models are fitted through the 165 month period, and taking under account that our cross-validation methodology fits hundreds of models to fit its best fit for every month, the climate dummy variable contains strictly no information that can be used by a machine learning algorithm to determine a bond's pricing. This allows us to conclude that climate bonds are not priced differently from traditional bonds. Variable importance for our new model permutations are available in table 4.

Table 4

Variables	Elastic Net	PCR	PLS	Mean
timetomat	0.37	1.00	1.00	0.79
betaRMW	0.56	0.45	0.89	0.63
meangrade	0.48	0.44	0.80	0.57
betaMktRF	0.17	0.50	0.96	0.54
MKTbond	1.00	0.03	0.36	0.46
VaR	0.23	0.40	0.76	0.46
betaMom	0.11	0.41	0.82	0.45
betaSMB	0.07	0.36	0.77	0.40
betaterm	0.04	0.37	0.64	0.35
betaHML	0.08	0.29	0.64	0.34
betadef	0.08	0.29	0.58	0.32
maxday	0.33	0.14	0.42	0.30
mom12m	0.34	0.17	0.37	0.30
realindmom	0.39	0.12	0.30	0.27
mom36m	0.13	0.18	0.42	0.24
size	0.11	0.35	0.23	0.23
ILLIQ	0.12	0.16	0.39	0.22
mom1m	0.40	0.05	0.19	0.21
betaCMA	0.09	0.16	0.36	0.20
betaAgg.Liq.	0.17	0.09	0.21	0.15
momt6t1	0.03	0.15	0.27	0.15
sd_turn	0.00	0.30	0.10	0.13
chmom	0.17	0.02	0.20	0.13
climate	0.00	0.00	0.00	0.00

Conclusion

As the use of Machine Learning methods is progressively growing in popularity amongst financial academics, we dedicate this study to the exploration of these methods when applied to the pricing of corporate bonds, and use a climate dummy variable to determine whether the fact that a corporate bond's issuer is climate-aligned has an impact on the pricing of this corporate bond. We first run our different models without the climate dummy variable and find that time to maturity predictor that is most used by our ML algorithms. We also find insightful results relative to the bond-specific risk factors developed in Bai, Bali and Wen (2019), as three of these factors are amongst the most used, while the authors' liquidity risk factor is amongst the less used predictors. Both stock market betas and corporate bond market betas are also used by the ML algorithms in a recurring manner. To date, however, only one of our ML method successfully obtains positive average out-of-sample R-squared over the entire test period.

Adding a climate dummy variable worsens our results and brings all our average out-of-sample R-squared into negative territory over the test period. However, adding the climate dummy variable does provide us with interesting insights: the climate dummy variable is by far the least used variable by our

ML algorithm and is barely used over hundreds of models fits. This indicates that the fact that a corporate bond is issued by a climate-aligned firm has no influence on its pricing.

This study is only an introduction to the possibilities that are provided by machine learning methods to understand the pricing of corporate bonds by market participants and to understand what differences may exist between climate-aligned firms and their traditional equivalents, as it has some important limitations. Firstly, the author's limited computational power prohibits him, to date, from applying more complex non-linear machine learning methods to this data, such as Random Forest or Neural Networks methods, which usually provide better results. These limitations in terms of computational power also restricts the author in integrating more predictors, specifically volatility, liquidity and macro-economic predictors that have been taken under account in Gu, Kelly and Xiu (2020). Finally, as aforementioned, the corporate bond pricing literature is still much less developed than the stock pricing literature, which means that there might still be many predictors that have not yet been developed by academics in this sector that could successfully predict future corporate bond returns.

References

Atsalakis, G.S. and Valavanis, K.P., 2009. Surveying stock market forecasting techniques–Part II: Soft computing methods. *Expert Systems with applications*, *36*(3), pp.5932-5941.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5*(1), pp.31-56.

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

Bali, T.G., Cakici, N. and Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, *99*(2), pp.427-446.

Bao, J., Pan, J. and Wang, J., 2011. The illiquidity of corporate bonds. *The Journal of Finance*, *66*(3), pp.911-946.

Bessembinder, H., Kahle, K.M., Maxwell, W.F. and Xu, D., 2008. Measuring abnormal bond performance. *The Review of Financial Studies*, *22*(10), pp.4219-4258.

Bianchi, D., Büchner, M. and Tamoni, A., 2019. What Matters When? Time-Varying Sparsity in Expected Returns. *Time-Varying Sparsity in Expected Returns (August 17, 2019)*.

Butaru, F., Chen, Q., Clark, B., Das, S., Lo, A.W. and Siddique, A., 2016. Risk and risk management in the credit card industry. *Journal of Banking & Finance*, *72*, pp.218-239.

Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of finance*, *52*(1), pp.57-82.

Chang, P.C., Liu, C.H., Lin, J.L., Fan, C.Y. and Celeste, S.P., Ng.(2009). *A neural network with a case based dynamic window for stock trading prediction. Expert Systems with Applications*, *36*(3), pp.6889-6898.

Chen, W.S. and Du, Y.K., 2009. Using neural networks and data mining techniques for the financial distress prediction model. *Expert systems with applications*, *36*(2), pp.4075-4086.

Chordia, T., Subrahmanyam, A. and Anshuman, V.R., 2001. Trading activity and expected stock returns. *Journal of financial Economics*, *59*(1), pp.3-32.

De Prado, M.L., 2018. *Advances in financial machine learning*. John Wiley & Sons.

Dick-Nielsen, J., 2009. Liquidity biases in TRACE. *The Journal of Fixed Income*, *19*(2), pp.43-55.

Dick-Nielsen, J., 2014. How to clean enhanced TRACE data. *Available at SSRN 2337908*.

Doeksen, B., Abraham, A., Thomas, J. and Paprzycki, M., 2005, April. Real stock trading using soft computing models. In *International Conference on Information Technology: Coding and Computing (ITCC'05)-Volume II* (Vol. 2, pp. 162-167). IEEE.

Fama, E.F., 1991. Efficient capital markets: II. *The journal of finance*, *46*(5), pp.1575-1617.

Filkova, M., Boulle, B., Frandon-Martinez, C., Giorgi, A., Giuliani, D., Meng, A. and Rado, G., 2018. Bonds and Climate Change. The State of the Market 2018. *Climate Bonds Initiative*.

Freyberger, J., Neuhierl, A. and Weber, M., 2017. Nonparametric Dissection of the Cross-Section of Expected Stock Returns. *NBER working paper*, *23227*.

Gettleman, E. and Marks, J.M., 2006. Acceleration strategies. *SSRN Electronic Journal*.

Giglio, S. and Xiu, D., 2017. *Inference on risk premia in the presence of omitted factors* (No. w23527). National Bureau of Economic Research.

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

Harvey, C.R. and Liu, Y., 2019. Lucky factors. *Available at SSRN 2528780*.

Heaton, J.B., Polson, N.G. and Witte, J.H., 2017. Deep learning for finance: deep portfolios. *Applied Stochastic Models in Business and Industry*, *33*(1), pp.3-12.

Henrique, B.M., Sobreiro, V.A. and Kimura, H., 2019. Literature review: Machine learning techniques applied to financial market prediction. *Expert Systems with Applications*, *124*, pp.226-251.

Huang, C.J., Yang, D.X. and Chuang, Y.T., 2008. Application of wrapper approach and composite classifier to the stock trend prediction. *Expert Systems with Applications*, *34*(4), pp.2870-2878.

Hutchinson, J.M., Lo, A.W. and Poggio, T., 1994. A nonparametric approach to pricing and hedging derivative securities via learning networks. *The Journal of Finance*, *49*(3), pp.851-889.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *The Journal of finance*, *45*(3), pp.881-898.

Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), pp.65-91.

Kelly, B.T., Pruitt, S. and Su, Y., 2017. Instrumented principal component analysis. *Available at SSRN 2983919*.

Kirczenow, G., Hashemi, M., Fathi, A. and Davison, M., 2018. Machine Learning for Yield Curve Feature Extraction: Application to Illiquid Corporate Bonds. *arXiv preprint arXiv:1812.01102*.

Khandani, A.E., Kim, A.J. and Lo, A.W., 2010. Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, *34*(11), pp.2767-2787.

Kozak, S., Nagel, S. and Santosh, S., 2017. *Shrinking the cross section* (No. w24070). National Bureau of Economic Research.

Malkiel, B.G., 2003. The efficient market hypothesis and its critics. *Journal of economic perspectives*, *17*(1), pp.59-82.

Malkiel, B.G. and Fama, E.F., 1970. Efficient capital markets. *A review of theory and empirical work Journal of Finance 25*, *383*, *417*.

Moritz, B. and Zimmermann, T., 2016. Tree-based conditional portfolio sorts: The relation between past and future stock returns. *Available at SSRN 2740751*.

Moskowitz, T.J. and Grinblatt, M., 1999. Do industries explain momentum?. *The Journal of finance*, *54*(4), pp.1249-1290.

de Oliveira, F.A., Nobre, C.N. and Zarate, L.E., 2013. Applying Artificial Neural Networks to prediction of stock price and improvement of the directional prediction index–Case study of PETR4, Petrobras, Brazil. *Expert Systems with Applications*, *40*(18), pp.7596-7606.

Pástor, Ľ. and Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. *Journal of Political economy*, *111*(3), pp.642-685.

Patel, J., Shah, S., Thakkar, P. and Kotecha, K., 2015. Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert systems with applications*, *42*(1), pp.259-268.

Rapach, D.E., Strauss, J.K. and Zhou, G., 2013. International stock return predictability: what is the role of the United States?. *The Journal of Finance*, *68*(4), pp.1633-1662.

Sarig, O. and Warga, A., 1989. Bond price data and bond market liquidity. *Journal of Financial and Quantitative Analysis*, pp.367-378.

Sirignano, J., Sadhwani, A. and Giesecke, K., 2016. Deep learning for mortgage risk. *arXiv preprint arXiv:1607.02470*.

Wright, D., Capriotti, L. and Lee, J., 2018. Machine learning and corporate bond trading. *Algorithmic Finance*, *7*(3-4), pp.105-110.

Appendix 1 - Model Monthly Performances

Month	OLS4 - *Roos*	OLS - *Roos*	Elastic Net - *Roos*	PCR - *Roos*	PLS - *Roos*	Glm - *Roos*
2012-02-01	0.000	-0.016	-0.007	0.000	-0.011	-0.016
2012-03-01	-0.124	-0.141	-0.075	-0.015	-0.145	-0.141
2012-04-01	-0.025	-0.078	-0.036	-0.042	-0.065	-0.078
2012-05-01	-0.013	-0.025	0.000	0.040	-0.046	-0.025
2012-06-01	0.030	0.045	0.046	0.018	0.037	0.045
2012-07-01	-0.001	0.032	0.012	0.026	0.045	0.032
2012-08-01	-0.044	-0.108	-0.032	0.040	-0.051	-0.108
2012-09-01	-0.007	0.001	0.006	-0.002	0.005	0.001
2012-10-01	0.010	-0.024	-0.016	-0.014	-0.034	-0.024
2012-11-01	0.022	0.039	0.029	0.028	0.036	0.039
2012-12-01	0.036	0.021	0.022	0.023	0.012	0.021
2013-01-01	-0.101	-0.107	-0.048	-0.005	-0.066	-0.107
2013-02-01	0.026	-0.023	0.004	0.026	0.027	-0.023
2013-03-01	-0.046	-0.106	-0.033	0.018	-0.017	-0.106
2013-04-01	-0.107	-0.031	-0.072	0.004	0.018	-0.031
2013-05-01	0.256	0.318	0.200	0.006	0.062	0.318
2013-06-01	-0.397	-0.406	-0.277	0.005	-0.343	-0.406
2013-07-01	-0.029	-0.044	-0.006	0.038	-0.007	-0.044
2013-08-01	-0.123	-0.296	-0.158	-0.044	-0.260	-0.296
2013-09-01	0.020	-0.087	-0.047	-0.047	-0.083	-0.087
2013-10-01	-0.078	0.038	0.015	0.062	0.078	0.038
2013-11-01	0.008	-0.167	-0.044	0.010	-0.014	-0.167
2013-12-01	-0.062	-0.136	-0.078	-0.123	-0.174	-0.136
2014-01-01	0.089	0.033	0.049	0.002	-0.003	0.033
2014-02-01	-0.002	-0.044	-0.032	-0.011	-0.039	-0.044
2014-03-01	-0.061	-0.097	-0.010	-0.017	-0.058	-0.097
2014-04-01	0.052	0.005	0.061	0.004	-0.013	0.005
2014-05-01	0.021	-0.016	-0.012	0.019	0.026	-0.016
2014-06-01	0.014	0.009	-0.034	-0.031	-0.046	0.009
2014-07-01	-0.121	-0.143	-0.024	0.011	-0.030	-0.143
2014-08-01	-0.129	-0.100	-0.148	-0.039	-0.042	-0.100
2014-09-01	-0.241	-0.346	-0.113	-0.003	-0.045	-0.346
2014-10-01	-0.007	-0.023	-0.025	-0.008	-0.008	-0.023
2014-11-01	-0.027	-0.071	-0.034	-0.006	-0.041	-0.071
2014-12-01	-0.020	-0.098	-0.001	0.007	-0.029	-0.098
2015-01-01	-0.073	0.011	-0.042	-0.009	0.027	0.011
2015-02-01	-0.046	-0.109	-0.026	-0.032	-0.041	-0.109
2015-03-01	0.041	-0.061	-0.031	-0.007	0.030	-0.061
2015-04-01	0.108	0.106	0.002	-0.037	0.006	0.106
2015-05-01	0.149	0.154	-0.034	-0.062	-0.020	0.154
2015-06-01	-0.064	-0.047	-0.050	-0.037	-0.072	-0.047
2015-07-01	-0.023	0.007	-0.131	-0.060	-0.088	0.007
2015-08-01	-0.032	-0.115	-0.036	-0.041	-0.059	-0.115
2015-09-01	-0.002	-0.054	0.015	0.013	0.020	-0.054
2015-10-01	-0.060	0.025	-0.146	-0.032	-0.051	0.025
2015-11-01	0.024	0.135	-0.030	-0.021	-0.033	0.135
2015-12-01	-0.017	0.033	0.026	-0.020	-0.018	0.033
2016-01-01	-0.031	-0.045	-0.012	-0.006	-0.014	-0.045
2016-02-01	0.096	0.058	-0.061	0.005	-0.022	0.058
2016-03-01	0.188	0.090	0.059	0.040	0.040	0.090
2016-04-01	0.001	-0.011	-0.002	0.011	0.013	-0.011
2016-05-01	-0.048	-0.088	0.070	0.045	0.041	-0.088
2016-06-01	0.126	0.111	0.114	0.039	0.054	0.111
2016-07-01	0.076	0.109	0.120	0.061	0.081	0.109
2016-08-01	0.039	0.020	-0.100	-0.029	-0.023	0.020
2016-09-01	0.103	0.069	-0.038	-0.041	-0.022	0.069
2016-10-01	0.166	0.124	0.022	-0.031	-0.011	0.124
2016-11-01	-0.264	-0.233	-0.055	0.031	0.045	-0.233
2016-12-01	0.014	0.001	0.014	0.015	0.015	0.001
2017-01-01	-0.030	-0.252	0.035	0.007	0.042	-0.252
2017-02-01	-0.073	0.034	-0.067	-0.035	-0.074	0.034
2017-03-01	-0.139	-0.489	-0.016	-0.002	0.016	-0.489
2017-04-01	0.021	-0.150	0.034	-0.008	0.030	-0.150
2017-05-01	-0.021	-0.072	0.014	-0.015	-0.028	-0.072

2017-06-01	-0.017	-0.058	-0.018	0.006	-0.001	-0.058
2017-07-01	-0.038	-0.057	0.016	-0.013	-0.028	-0.057
2017-08-01	0.068	0.005	-0.001	0.032	0.058	0.005
2017-09-01	0.036	-0.010	0.009	0.023	0.038	-0.010
2017-10-01	0.044	0.020	0.028	0.022	0.037	0.020
2017-11-01	-0.006	-0.060	0.054	0.034	0.056	-0.060
2017-12-01	0.045	0.076	0.040	0.030	0.054	0.076
2018-01-01	0.185	0.262	0.030	-0.010	-0.001	0.262
2018-02-01	0.040	0.071	0.015	-0.020	-0.040	0.071
2018-03-01	0.117	0.142	0.086	0.048	0.076	0.142
2018-04-01	-0.065	-0.213	-0.024	0.000	-0.014	-0.213
2018-05-01	0.046	0.152	0.011	0.024	-0.009	0.152
2018-06-01	-0.048	-0.250	0.013	0.024	0.034	-0.250
2018-07-01	-0.011	-0.086	-0.024	-0.021	-0.035	-0.086
2018-08-01	0.079	0.170	-0.013	0.054	0.002	0.170
2018-09-01	0.112	0.185	0.008	0.009	-0.017	0.185
2018-10-01	0.129	0.135	0.063	0.015	0.020	0.135
2018-11-01	-0.060	-0.039	-0.045	-0.044	-0.047	-0.039
2018-12-01	0.036	0.006	0.019	-0.032	-0.005	0.006
2019-01-01	0.068	0.064	0.064	-0.004	0.051	0.064
2019-02-01	-0.108	-0.232	-0.040	-0.073	-0.011	-0.232

Appendix 2 - Monthly Monthly Performances (With Climate Dummy Variable)

Month	OLS4 - *Roos*	OLS - *Roos*	Elastic Net - *Roos*	PCR - *Roos*	PLS - *Roos*	Glm - *Roos*
2012-02-01	0.000	-0.016	-0.007	0.001	-0.013	-0.016
2012-03-01	-0.124	-0.139	-0.075	-0.016	-0.144	-0.141
2012-04-01	-0.025	-0.078	-0.036	-0.037	-0.065	-0.078
2012-05-01	-0.013	-0.024	0.000	0.038	-0.046	-0.025
2012-06-01	0.030	0.044	0.046	0.016	0.039	0.045
2012-07-01	-0.001	0.032	0.012	0.025	-0.008	0.032
2012-08-01	-0.044	-0.109	-0.032	0.037	-0.056	-0.108
2012-09-01	-0.007	0.002	0.006	-0.003	0.007	0.001
2012-10-01	0.010	-0.023	-0.016	-0.013	-0.034	-0.024
2012-11-01	0.022	0.040	0.029	0.028	0.037	0.039
2012-12-01	0.036	0.022	0.022	0.024	0.011	0.021
2013-01-01	-0.101	-0.107	-0.048	-0.007	-0.064	-0.107
2013-02-01	0.026	-0.022	0.004	0.026	0.026	-0.023
2013-03-01	-0.046	-0.106	-0.033	0.016	-0.018	-0.106
2013-04-01	-0.107	-0.031	-0.072	0.006	0.018	-0.031
2013-05-01	0.256	0.318	0.200	0.008	0.062	0.318
2013-06-01	-0.397	-0.407	-0.277	0.004	-0.345	-0.406
2013-07-01	-0.029	-0.043	-0.006	0.038	-0.008	-0.044
2013-08-01	-0.123	-0.299	-0.158	-0.045	-0.261	-0.296
2013-09-01	0.020	-0.086	-0.047	-0.048	-0.084	-0.087
2013-10-01	-0.078	0.038	0.015	0.061	0.078	0.038
2013-11-01	0.008	-0.167	-0.044	-0.003	-0.014	-0.167
2013-12-01	-0.062	-0.138	-0.078	-0.157	-0.175	-0.136
2014-01-01	0.089	0.034	0.049	-0.003	-0.004	0.033
2014-02-01	-0.002	-0.044	-0.032	-0.050	-0.039	-0.044
2014-03-01	-0.061	-0.097	-0.010	-0.064	-0.059	-0.097
2014-04-01	0.052	0.004	0.061	-0.020	-0.014	0.005
2014-05-01	0.021	-0.015	-0.012	0.022	0.026	-0.016
2014-06-01	0.014	0.009	-0.034	-0.067	-0.045	0.009
2014-07-01	-0.121	-0.143	-0.024	-0.025	-0.031	-0.143
2014-08-01	-0.129	-0.098	-0.148	-0.032	-0.040	-0.100
2014-09-01	-0.241	-0.346	-0.113	-0.021	-0.046	-0.346
2014-10-01	-0.007	-0.025	-0.025	-0.009	-0.008	-0.023
2014-11-01	-0.027	-0.072	-0.034	-0.007	-0.041	-0.071
2014-12-01	-0.020	-0.100	-0.001	0.005	-0.030	-0.098
2015-01-01	-0.073	0.012	-0.042	-0.007	0.028	0.011
2015-02-01	-0.046	-0.110	-0.026	-0.032	-0.041	-0.109
2015-03-01	0.041	-0.061	-0.031	-0.007	0.031	-0.061
2015-04-01	0.108	0.107	0.002	-0.036	0.007	0.106
2015-05-01	0.149	0.154	-0.034	-0.060	-0.018	0.154
2015-06-01	-0.064	-0.048	-0.050	-0.035	-0.071	-0.047
2015-07-01	-0.023	0.007	-0.131	-0.059	-0.087	0.007
2015-08-01	-0.032	-0.118	-0.036	-0.033	-0.059	-0.115

2015-09-01	-0.002	-0.052	0.015	0.009	0.019	-0.054
2015-10-01	-0.060	0.023	-0.146	-0.027	-0.050	0.025
2015-11-01	0.024	0.135	-0.030	-0.020	-0.033	0.135
2015-12-01	-0.017	0.032	0.026	-0.020	-0.018	0.033
2016-01-01	-0.031	-0.044	-0.012	-0.007	-0.015	-0.045
2016-02-01	0.096	0.059	-0.061	0.005	-0.022	0.058
2016-03-01	0.188	0.094	0.059	0.042	0.040	0.090
2016-04-01	0.001	-0.010	-0.002	0.009	0.012	-0.011
2016-05-01	-0.048	-0.088	0.070	0.045	0.041	-0.088
2016-06-01	0.126	0.111	0.114	0.039	0.054	0.111
2016-07-01	0.076	0.110	0.121	0.061	0.081	0.109
2016-08-01	0.039	0.022	-0.099	-0.029	-0.023	0.020
2016-09-01	0.103	0.071	-0.038	-0.041	-0.055	0.069
2016-10-01	0.166	0.124	0.022	-0.032	-0.021	0.124
2016-11-01	-0.264	-0.232	-0.054	0.032	0.047	-0.233
2016-12-01	0.014	0.001	0.013	0.015	0.014	0.001
2017-01-01	-0.030	-0.253	0.036	0.007	0.044	-0.252
2017-02-01	-0.073	0.034	-0.069	-0.036	-0.078	0.034
2017-03-01	-0.139	-0.486	-0.013	-0.003	0.019	-0.489
2017-04-01	0.021	-0.153	0.033	-0.008	0.031	-0.150
2017-05-01	-0.021	-0.072	0.014	-0.016	-0.028	-0.072
2017-06-01	-0.017	-0.058	-0.017	0.007	0.000	-0.058
2017-07-01	-0.038	-0.058	0.016	-0.014	-0.029	-0.057
2017-08-01	0.068	0.006	-0.001	0.032	0.059	0.005
2017-09-01	0.036	-0.010	0.011	0.022	0.039	-0.010
2017-10-01	0.044	0.020	0.027	0.021	0.036	0.020
2017-11-01	-0.006	-0.060	0.054	0.033	0.057	-0.060
2017-12-01	0.045	0.079	0.040	0.030	0.055	0.076
2018-01-01	0.185	0.261	0.030	-0.009	-0.002	0.262
2018-02-01	0.040	0.071	0.014	-0.019	-0.040	0.071
2018-03-01	0.117	0.143	0.086	0.045	0.076	0.142
2018-04-01	-0.065	-0.214	-0.025	0.001	-0.014	-0.213
2018-05-01	0.046	0.152	0.009	0.023	-0.010	0.152
2018-06-01	-0.048	-0.249	0.015	0.025	0.038	-0.250
2018-07-01	-0.011	-0.087	-0.022	-0.009	-0.035	-0.086
2018-08-01	0.079	0.170	-0.011	0.047	0.003	0.170
2018-09-01	0.112	0.185	0.008	0.034	-0.018	0.185
2018-10-01	0.129	0.135	0.063	0.027	0.020	0.135
2018-11-01	-0.060	-0.040	-0.046	-0.029	-0.047	-0.039
2018-12-01	0.036	0.004	0.029	-0.037	-0.005	0.006
2019-01-01	0.068	0.066	0.065	-0.006	0.050	0.064
2019-02-01	-0.108	-0.234	-0.040	-0.082	-0.009	-0.232