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Prediction-based Investment Strategies in European Bond Markets

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Abstract Daily returns of the European corporate bond market are predicted using a penalized Lasso regression or Random forests. Predictions are utilized in investment strategies that allocate resources into risky position: interest-rate hedged corporate bonds or unhedged corporate bonds and risk-free position proxied by the Euro-Bobl futures that track the German government bonds. The strategies are more profitable with a lower risk than their passive alternatives, which only invest in corporate bonds (hedged or unhedged), but the daily rebalancing can be costly. Therefore, we examine the break-even transaction costs and suggest two approaches to lower the overall costs. Overall, even with costs, active strategies based on prediction can achieve higher returns with a lower risk.

Keywords corporate bonds, credit spread, machine learning, asset allocation, investing strategy.

1. INTRODUCTION

Prices of both government and corporate bonds are determined by corresponding cash flows and time to maturity, but both reflect the probability of default. On average, corporate bonds have a higher probability of default than government bonds that are often regarded as risk-free investments (at least for the most developed economies in the world, such as Germany or the US). Naturally, investors require a higher return for bearing the risk of investing in corporate bonds, and the difference is usually considered to be the spread between safer government bonds and their riskier peers. In other words, the yield of every bond could be decomposed into the risk-free part (government yield) and credit spread (CS) as compensation for a higher risk.

Although the returns of corporate bonds are expected to be higher, bond prices are constantly changing based on the demand and supply in financial markets. For example, high demand for safe assets or risk-aversion in the markets can easily cause a sharp increase in government bond prices and a sharp fall in riskier corporate bonds simultaneously. On the other hand, the risk-on appetite can push the riskier bonds up. Therefore, mark-to-market bond prices constantly fluctuate based on the market's situation, and selling the bond before maturity can cause significant gains or losses.

The credit spread fluctuations and stressed periods open the question of whether it is possible to make predictions and a rule-based decision if investing in corporate or government bonds is preferable. Despite the ever-developing topic, the problem of risky or risk-free asset allocation is well documented in the literature. Still, the researchers are most interested in the equity market as a risky investment or the asset class allocation problem. A novel trend is to incorporate as much information as possible using machine learning methods that, compared to simple linear regression, have several benefits, such as variable selection, robustness, overfit, or the ability to describe non-linear patterns. The algorithms include Random Forests (Benhamou et al., 2020), neural networks (Babiak and Barunik, 2021), or several methods at the same time, such as Wolff and Echterling (2020) who compared the PCA and regularized regressions: Ridge, Lasso, and Elastic net, Random Forests, Boosting, DNN and LSTM neural networks for a prediction which 50 stocks will outperform S&P 500 or STOXX Europe 600 indexes.

Although ML techniques are increasingly adopted to predict risky assets, the bond market is marginal. We aim to fill the gap in the literature by studying to which extent the European bond market can be predicted. Our research is closely related to Amenc et al. (2003), who studied the US bond market and predicted the monthly return using linear regression with pre-chosen economically meaningful variables, according to the authors.

The European corporate bond market is proxied by the widely followed Bloomberg Euro Corporate Bond Index that is easily investable through ETFs. The government bonds are proxied by Euro-Bobl futures based on a basket of medium-term (4.5-5.5 years) debt issued by the German government. The choice of the investment universe ensures that both assets are investable and liquid with efficient trading costs. Furthermore, the usage of futures allows taking a short position in treasury bonds, thus a possibility to hedge the interest rate. The hedged position offers a way to harvest the credit spread with a lower duration risk.

Regarding predictors, we study a large set of fundamental and technical variables and let the statistical methods select the variables. The motivation is to utilize interpretable ML techniques and perform a thorough explanatory analysis of variable importance. Additionally, there is potential to obtain a better prediction by unbiasedly choosing numerous variables suggested in the literature (even among other asset classes).

We examine the possibility of predicting the daily return of either the corporate bond index or the interest-rate hedged corporate bond index (credit spread). Predictions are based on fundamental and technical data such as implied volatilities, yield curve properties, moving averages, and several statistical attributes of the market without a look-ahead bias. The methods include Lasso regression and Random forests since both methods provide insight into the importance of the variables used for predictions. Subsequently, both approaches are utilized in an investment strategy that allocates into riskier (un)hedged corporate bonds or safer government bonds, considering the predicted return. A thorough analysis of transaction costs further examines the practical feasibility. Several approaches are offered, such as rebalancing if the predicted return is higher than anticipated costs or less frequent weekly rebalancing.

2. DATA

The corporate bond market is proxied by the Bloomberg Euro Corporate Bond Index with an average maturity of approximately five years. The index is easily investable in the market, e.g., by buying iShares Core € Corp Bond UCITS ETF. The government bond universe is tracked by the Euro-Bobl futures, which have a basket of medium-term 4.5-5.5 years bonds issued by the German government as the underlying asset. The data spans from 6.4.2009 to 25.1.2021. The interest rate hedged corporate bonds are proxied by a long position in the corporate index and an equal short position in the futures. Therefore, the hedged investment is equivalent to the long position in credit spread that is defined as the difference between daily realized return of corporate bonds and German government bonds:

$$\text{creditspread}_{j,t} = r_{corp,j,t} - r_{futures,j,t}. \quad (1)$$

The variables used for predictions include implied volatility indexes VDAX (DAX index) and VIX (S&P 500 index), commonly referred to as the fear index calculated from options. Although VIX is linked to the US stock market, it can be an excellent global proxy in the era of globalization, while the VDAX is linked to the German stock market with a premier position in the Eurozone. Although volatility indexes are indicators of the investor's expectations regarding the volatility of main equity indexes, corporate bonds and equities are linked since both represent claims to assets of the firm (Merton, 1974). As another uncertainty measure, we employ the Merrill Lynch Option Volatility Estimate (MOVE) index, which is related to the implied volatility of US treasuries with a maturity of 2, 5, 10, and 30 years. Unfortunately, the comparable European index is not timely published, but the methodology was presented and constructed for past data (Baran and Voříšek, 2020). For volatility indexes, we evaluate the absolute values and daily changes (from t to t-1). For the VIX and VDAX, we also evaluate the intensity of change defined as the daily change scaled by the value of the index at day t. The data include open prices at day t to predict price change at day t+1 (from market close at t to market close at t+1) to avoid look-ahead bias.

Secondly, we include information from the foreign exchange market - the EUR/USD spot rate, as the dollar is the world's reserve currency and is considered a safe haven. Euro is also regarded as the safe haven, and the hedging properties of EUR or USD also depend on the investor's country. USD is a better hedge for Asia and Latin America, while Euro is a better hedge for emerging European countries (Beck and Rabhari, 2008). The variables include the change over the previous 1, 5, 10, and 20 days and the last known spot rate for the model is from the previous day's open.

One of the key concepts in quantitative investing is the trend following or momentum, e.g., in asset class picking (Faber, 2013), S&P 500 investing (Beaudan and He, 2019), or corporate bonds predictions (Kaufmann et al., 2021) and Guo et al. (2021). Therefore, we include the past credit spread moving averages of 5, 10, 15, and 20 days with a two-day lag as the data is sampled at the market's close.

The variables also include the three months EURIBOR as short-term rates are one of the key policy instruments of central banks (Diebold et al., 2005) and proxy for expected inflation (Fama, 1975). The short rates are expected to influence the long-term rates since the bond yield consists of the actual rate, expected rate, and term premium (Brooks, 2021). Furthermore, the three-month risk-free rate changes affect credit spreads (Astrid Van Landschoot, 2004). While the short rate is often the starting point of a yield curve, other components such as level (three-month rate) and slope (the difference between the 10-year yield and 3-months rate) were also found to be significant (Astrid Van Landschoot, 2004). More traditionally, the yield curve level is defined as the yield of the longer maturity 10-year bond and the slope as the difference between the 10-year yield and 3-months rate (Diebold and Li, 2006). Therefore, the variables include the level and slope of the German yield curve based on the previous day's open prices and the daily changes of both level and slope.

Lastly, we include several statistical characteristics such as standard deviation (volatility) and skewness. Credit spread volatility is an indicator of return dispersion. It can signal a higher expected return according to a classical economic theory where an investor should be compensated for increased risk (Sharpe, 1964). On the other hand, cross-sectionally, low-volatility assets outperform high-volatility assets (Blitz and Vliet, 2007). The predictors include the volatility of credit spread based on the past 10, 15, and 20 days with a lag of two days to avoid the look-ahead bias. We also estimate the volatility of indexes VIX and VDAX since the past realized volatility of volatility expectations (implied volatility) can indicate periods with a high dispersion of market expectations. The volatility is estimated on the past 10, 15, and 20 days based on open prices. From the statistical characteristics, we also employ the realized skewness since it was found to be a reliable predictor across several asset classes such as individual stocks (Amaya et al., 2015), equity indexes (Zaremba and Nowak, 2015) or commodities (Fernandez-Perez et al., 2018). According to the theory, assets with large skewness have fat tails and a small probability of high returns, which investors behaviorally perceive as attractive. Subsequently, these assets are overpriced with low expected returns. The skewness is estimated for corporate bonds, government bonds, and credit spread individually, based on the past 20 days with a two-day lag.

Empirically, the fluctuations can be observed by plotting the moving average of the return difference between corporate and government bonds, where the returns are directly computed from bond prices. We expect that in crises, the riskier bonds will underperform their safer government alternative as the result of higher demand for safe-haven assets and risk-off sentiment. Therefore, in Figure 1, we plot the moving average with highlighted crisis periods defined as periods of heightened implied volatility in the European bond market (Baran and Voříšek, 2020) and the corona crisis. The periods include default fears, several key ECB announcements, Brexit, and other political crises. For a fundamental reasoning behind these crises, we refer to Baran and Voříšek.

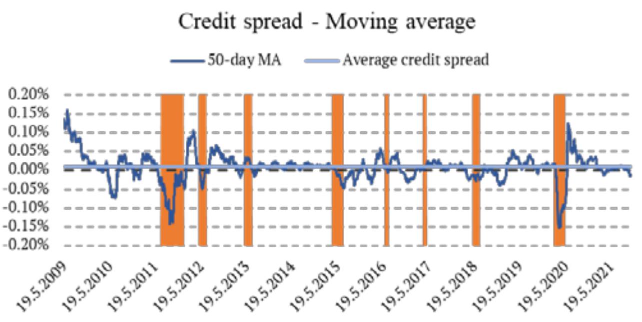

Figure 1: Credit spread development. The sample period spans from 19.5.2009 to 21.10.2021. Crises are highlighted.

On the one hand, the credit spread is positive, and corporate bond investors are compensated for their higher risk in the long run. On the other hand, there are several periods where corporate bonds significantly underperform, and many coincide with crises. Moreover, periods of credit spread underperformance occur when the interest-rate hedged corporate bond position suffers. Notably, the periods with risk-off sentiment where corporate bonds decline with an immense interest in safe havens create a scenario where credit-spread harvesting is mainly unprofitable. The reason is that hedging is getting more expensive and is not compensated by higher corporate bond returns.

3. PREDICTIONS AND APPLICATION

3.1 Prediction

Based on both fundamental and technical variables outlined in the previous section, we aim to predict the next day's credit spread or corporate bond return. The problem can be defined as follows:

$$\widehat{r_{t+1}} = f(\theta, x). \tag{2}$$

The function f and parameters are model-dependent, and x are explanatory variables that are known at time t or sooner. Each explanatory variable is rescaled by min-max normalization.

Regarding the methods used, we utilize the Lasso regularized regression, which can shrink coefficients, has a variable selection property and should be more robust. Regression is estimated in R using the package "glmnet," and the optimal lambda parameter of the Lasso is found by cross-validation (Friedman et al., 2010). Random forests are used as a second method for comparison since this method is non-linear and alleviate the problems with single trees that tend to be overfitted. Random forest trains several trees where each tree can have a distinct training dataset, and the result is aggregated across the trees. For Random forests hyperparameters we set the number of trees to 500 and explore several variants of variables randomly sampled as candidates at each split: 12, 18, and 24. Trees are trained in R using the "randomForest" package (Liaw and Wiener, 2002).

The training dataset is expanding, i.e., we first train the model based on the first 200 days of the sample, and the following 20 days are used for the out-of-sample test. Then we add these 20 days to the training set, train the models based on 220 days, and leave the subsequent 20 days for the out-of-sample test. We iteratively continue until the end of the sample.

From a statistical perspective, we evaluate the mean squared error, accuracy, and weighted accuracy. Let n be the number of predictions, $\hat{y}$ the predicted return, and y_i the real market return. We define the accuracy based on the correct sign of prediction so that the prediction is accurate when credit spread (corporate bonds return) is positive (negative) if the realized return is positive (negative):

$$\text{Acc} = \frac{1}{n}\sum_{i=1}^{n} 1_{\text{sign}(\hat{y}_i)=\text{sign}(y_i)}. \tag{3}$$

The weighted accuracy is weighted by the magnitude of the return since, from the economic point of view, it is more vital to predict larger returns (losses) correctly:

$$\text{Acc}_w = \frac{1}{\|y\|_1}\sum_{i=1}^{n} 1_{\text{sign}(\hat{y}_i)=\text{sign}(y_i)} \times |y_i|. \tag{4}$$

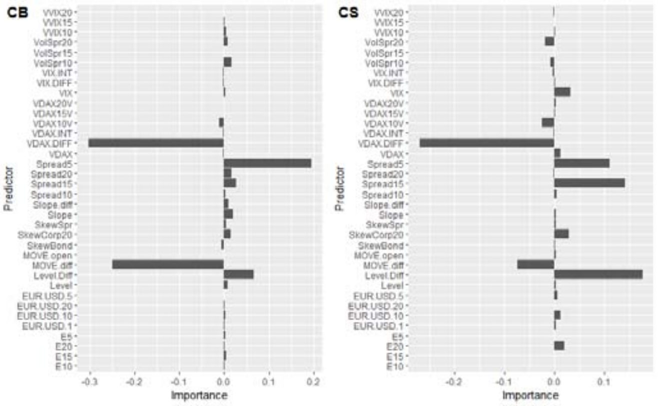

Figure 2: Most essential predictors for corporate bonds (CB) and credit spread (CS).

The methods can also reveal which variables are most important for the predictions. Hence, we can examine which variables mostly affect the expected performance of either corporate bonds or credit spreads. Since all variables are standardized, for Lasso regression, the importance of the variable is defined as the average coefficient from the regression over all training sets divided by the sum of the absolute values of all coefficients. Such a definition informs us not only about the magnitude of influence in the prediction (absolute value of importance measure) but also if the predictor's value is negative or positive, e.g., if the importance is negative (positive). It means that the higher values predict a smaller (higher) subsequent performance. We only plot results for Lasso regression, but the results for Random forests can be obtained using the "randomForest" package (Liaw and Wiener, 2002) in R and are qualitatively comparable.

According to Figure 2, the essential variable for the prediction of both corporate bonds and credit spread is the daily change of VDAX, which affect the subsequent returns negatively, whereas the absolute value of the index or the intensity has only a minor prediction ability. Another critical variable is the MOVE index's daily change (difference), but it is more significant for corporate bonds than credit spread. The importance is reversed for the difference in the yield curve level, which is a major variable for credit spread but has a lesser importance for corporate bonds. Since the credit spread has an embedded short position in government bonds, it is in line with economic intuition that the yield curve-related variable is an important predictor. For both types of prediction, the past spreads also significantly influence the expected performance, and the model indicates a return continuation (momentum) since the sign is positive. Although the importance of other variables is minor, their cumulative contribution is not negligible.

As shown in Table 1, the statistical accuracy is comparable across both methods for credit spread and corporate bond predictions. Furthermore, the accuracy is more significant than 50%, an essential benchmark since the performance is better than the random decision of whether the market would go up or down. The promising statistical accuracy of the predictions, and the fact that the weighted accuracy is, in fact, higher than the naive one, raise a question if it is possible to employ the aforementioned predictions in financial practice.

Panel A: Credit spread				
	Lasso	**RF(500,12)**	**RF(500,18)**	**RF(500,24)**
Acc	0,595	0,584	0,585	0,579
Acc_w	0,62	0,602	0,615	0,605
MSE	$1{,}511\times 10^{-6}$	$1{,}849\times10^{-6}$	$1{,}908\times10^{-6}$	$1{,}872\times10^{-6}$
Panel B: Corporate bonds				
	Lasso	**RF(500,12)**	**RF(500,18)**	**RF(500,24)**
Acc	0,587	0,576	0,582	0,58
Acc_w	0,638	0,632	0,634	0,637
MSE	$2{,}442\times10^{-6}$	$2{,}796\times10^{-6}$	$2{,}859\times10^{-6}$	$2{,}83\times10^{-6}$

Table 1: Statistical accuracy of predictions.

3.2 Market timing strategies

Based on the accuracy of the predictions, we propose a straightforward trading rule: if the predicted return of corporate bonds (credit-spread) is positive, invest in corporate bonds (credit-spread), and if the predicted return is negative, invest in government bonds. The proposed market-timing strategy aims to allocate risky assets (corporate bonds, either hedged or not) or safe assets proxied by government bonds. However, such a trading rule needs more practical feasibility since the strategy can rebalance itself daily, which could cause substantial trading costs. Still, the majority of research is mainly focused on the theoretical world – without any transaction costs or the need to employ some lag in the decision process. Nevertheless, some literature considers the feasibility and transaction costs, e.g., break-even costs when the strategy is still profitable and sufficient lag in the data (Blitz et al., 2022). Therefore, we study the break-even transaction costs when the strategy is still profitable compared to the alternatives – passively hedged corporate bonds or corporate bonds. Next, we suggest two approaches to lower the overall transaction costs. In all scenarios, we examine five levels of transaction costs from 1 basis point to 5 basis points (bp). For the first approach, the strategies can be rebalanced less frequently, e.g., every five trading days (weekly). Secondly, we suggest a tactical approach where the strategies are rebalanced only if the predicted return is higher than the expected transaction costs. Therefore, the strategy switches if the predicted return is 3bp and the costs are assumed to be 2bp. However, if the predicted return is -1bp and the costs are assumed to be 2bp, the strategy does not rebalance.

For credit spread predictions, the market timing strategy becomes unprofitable if the transaction costs are 5bp and is less profitable than passively interest-rate hedged corporate bonds if costs are 4bp. On the other hand, if costs are 3bp or lower, the prediction-based strategy is more profitable even without any approach to mitigate the effect of costs. Based on Figure 3, both approaches that aim to lower overall transaction costs can do so successfully, but the tactical approach relates to a lower risk than less frequent rebalancing. The effect of transaction costs for corporate bond strategies is similar. According to Figure 4, all tactical approaches are better than their passive alternative, which also holds for the majority of less frequently rebalanced strategies. Moreover, the predicted strategies are significantly less risky than a passive investment in corporate bonds.

The attractive property of prediction-based strategies is their ability to decrease risk, which is the result of successfully switching between riskier and safer investments. For example, for credit spread timing strategies, the risk measured by volatility is similar to the passive credit spread investing, but the maximal drawdown is much lower (Figure 3). The lower risk is even more evident among corporate bonds, where both volatility and maximal drawdown are lower (Figure 4). For both investment universes, the lower drawdowns and more stable returns can be observed by inspecting Figure 5, which shows the simulated performance of investment portfolios based on the market timing strategies.

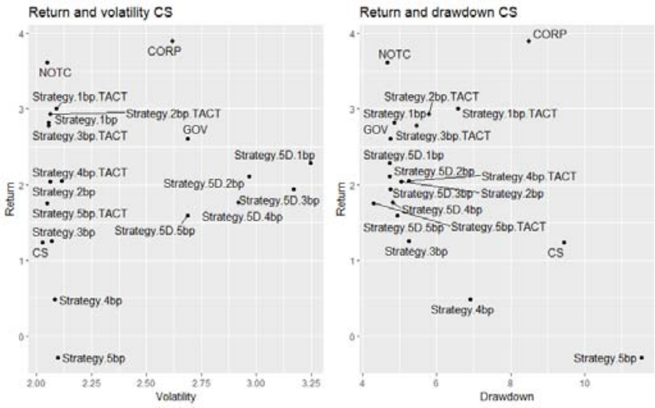

Figure 3: Return, volatility, and maximal drawdown of credit spread strategies based on Lasso predictions. CORP stands for corporate bonds, CS stands for credit spread, government bonds are denoted as GOV, theoretical strategy without transaction costs as NOTC, strategies with a tactical approach to rebalancing as TACT, and strategies with weekly rebalancing as 5D. Returns and volatilities are annualized in percentage points. Maximal drawdown is denoted as a positive number in percentage points. Results for random forests are available but unpublished and qualitatively comparable.

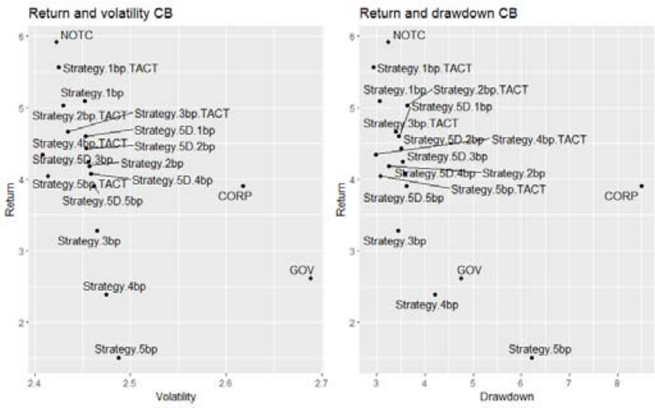

Figure 4: Return, volatility, and maximal drawdown of corporate bond strategies based on random forests (500,12) predictions. CORP stands for corporate bonds, CS stands for credit spread, government bonds are denoted as GOV, theoretical strategy without transaction costs as NOTC, strategies with a tactical approach to rebalancing as TACT, and strategies with weekly rebalancing as 5D. Returns and volatilities are annualized in percentage points. Maximal drawdown is denoted as a positive number in percentage points. Results for Lasso are available but unpublished and qualitatively comparable.

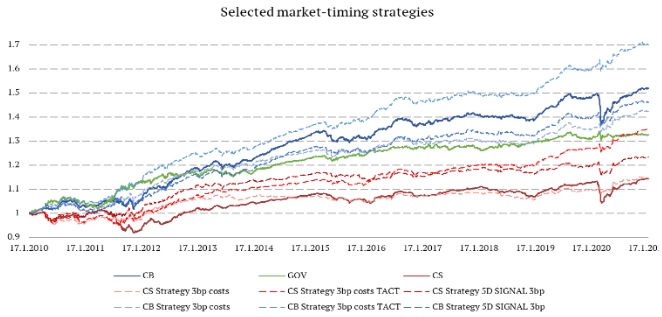

Figure 5: Performance development of selected prediction-based market-timing strategies.

4. CONCLUSION

On average, corporate bond returns are higher than government bonds. However, the outperformance does not remain constant. There are periods when corporate bonds are less profitable than government ones, coinciding with periods when credit-spread investing has been unprofitable. We have shown that both the corporate bond market and credit spread (interest-rate hedged corporate bonds) have been predictable to the extent that it has been possible to include the predictions in asset allocation decisions. We have obtained accurate predictions of the next day's return using either Lasso regression or random forests based on several fundamental and technical variables without look-ahead bias. The choice of the methods has allowed us to examine the most critical variables, which include the daily change in the DAX implied volatility, change in the level of the yield curve, changes in the implied volatility of the US bond market, and moving averages of past credit spreads.

The predictions could have been used in practice by constructing trading strategies that have invested in risky (credit spread or corporate bonds) and safe assets (government bonds) based on the predicted return. Furthermore, we have evaluated the effect of transaction costs and suggested two approaches to minimize the costs: less frequent rebalancing and a tactical approach where the strategies have only rebalanced if the predicted return has been greater than the anticipated costs. Firstly, we have identified the level of transaction costs that has eroded the performance to the extent of making it less profitable than a passive investment in corporate bonds or credit spreads. Secondly, we have shown that the less-frequent rebalancing and the tactical approach have significantly lowered transaction costs and maximized the strategy's returns. Overall, the tactical approach has been superior since, for both credit-spread and corporate bond strategies, even the 5bp costs would not have made the strategy less profitable than passive investment into credit-spread or corporate bonds.

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