Executive Summary

Problem

The lack of transparency in the corporate bond market, led to the establishment of the first Credit Rating Agencies in the beginning of the 20th century. They would assess the creditworthiness of issuers and then provide valuable information for investors interested in the affairs of the companies they have invested in. These agencies gained major importance due to increasing demand for ratings caused by their favorable reputation and regulatory relevance, especially after the 1960s (Kon, 2018). At this time, the question of whether their significance was big enough to influence to financial market arose. Early studies examined the effect of credit rating changes on the stock and bond market and found impactful results. In the meantime, researchers and practitioners started to develop statistical - and later machine learning - models trying to replicate and predict future credit ratings, as this would contribute to an investors technical analysis.

Despite the fact that countless studies predicting credit ratings have been conducted, very few researchers have addressed the prediction of credit migration. Furthermore, most studies only use financial variables for the prediction, neglecting the business risk directly incorporated in credit rating determination. This thesis primarily seeks to identify factors apart from financial and accounting ratios that can be used as a proxy of business risk. The main objective is to develop a machine learning model predicting corporate credit rating downgrades that can be used as an alert tool for investors, holding corporate bonds and equities in their portfolio.

Method

The determination of factors affecting the financial and business risk of an issuer is achieved through an extensive literature research. The study then uses the random forest method to implement the prediction model. Two samples containing data of corporate issuers are used for training purposes. More specifically the first sample consists of quarterly accounting data fetched from Capital-IQ. The second sample is enriched with two additional factors: four analysts' estimates from Capital-IQ and a news sentiment score from the RepRisk database. Furthermore, the data in the second data sample is timestamped according to the announcement date and not according to of the end of each quarter, in contrast to the first sample.

Results

The model was tested on both samples as well as on subsamples. The obtained overall prediction accuracy lies between 95% and 98% indicating good performance. For the first sample, the highest accuracy is achieved when all features are given as an input whereas in terms of precision, i.e. the accuracy of predicted downgrades, the results obtained if one uses exclusively the Standard and Poor's credit watch indicator are by far the best. This is also the case for the second data sample. On the contrary, when using the second sample, the highest overall accuracy is achieved if only the 50% most important features are used for training purposes. The precision however, is still the highest if one only considers the Standard and Poor's (S&P's) credit watch.

As the accuracy in terms of precision does not exceed 50%, a slightly altered approach is proposed. It is suggested to focus on the downgrade probabilities computed by the model rather than the prediction outcome. This would allow an investor to use the model as an alert tool, indicating which issuers are likely to be downgraded and should therefore, be examined further.

Evaluation

This study is one of the few to consider both quantitative and qualitative values for a credit rating downgrade prediction. As no exact benchmark with which to compare the obtained results exists, it is difficult to assess the performance of the model. Researchers such as Kunz (2018) addressing the similar research question came across various limitations, especially linked the selection of the prediction model. Several possible research ideas are further conceivable. It would be particularly interesting to include additional qualitative factors in the model to account for the business risk of the issuer. Further, other machine learning techniques, such as Artificial Neural Networks or Support Vector Machines can be implemented and tested on the same data sets. Finally alternative approaches to tackle the issue of the imbalanced data could be examined. The author recognizes the value of this study and suggests that it is regarded as a useful tool, constituting the foundation for possible further investigation, as it cannot replace the expert practitioner.