**Estimating credit risk premiums with neural networks**

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# 1.1 Introduction

A fundamental concept in financial economics is the risk/return trade off. Investors expect to earn a higher return on a risky investment as compared to an investment with a lower level of perceived risk. While some exceptions to this rule have been observed, generally this is a widely accepted phenomenon in financial markets (Ghysels, Santa-Clara and Valkanov, 2005). For example, the interest earned on a bank account is extremely low because the depositor has access to the funds immediately and the deposits are guaranteed by government backed insurance providers. The interest earned on a corporate bond, however, would generally be significantly higher than interest on a bank account because there is a risk the corporation may find itself unable to pay back the bond, and because unlike bank deposits, bonds cannot easily be converted into cash.

The difference in return between an investment that is risk-free versus an investment that is risky is referred to as the risk premium. With regard to corporate bonds, there are various sources of risk that contribute to the risk premium. Macroeconomic factors such as inflation and central bank interest rates, as well as microeconomic factors such as the risk of corporate default. In his seminal 1959 study in risk premiums, Lawrence Fisher identified the following factors that contribute to microeconomic risk premiums: Earnings Variability, Period of solvency, Equity/Debt Ratio, Bonds Outstanding, Volume of Trading and Ratio of standard deviation in earnings to equity (Fisher, 1959). These variables capture two sources of risk: The risk that a corporate borrow will not be able to repay their loans, known as Credit Risk, and the risk that an investor will not be able to sell or redeem a bond for cash easily if needed, known as Liquidity Risk. Fisher found that approximately 75% of the risk premium on corporate bonds could be estimated using a simple linear regression model on the variables mentioned above.

Risk premiums are fundamental to pricing or valuing investments. The role of an investment analyst is to estimate the risk premium for any given investment. And yet, there is no model that can perfectly estimate the appropriate risk premium for a particular investment. The unpredictability of economic outcomes ensures estimating risk premiums remains as much an art as a it is a science. Due to the empirical nature of investment valuation, machine learning may lend itself nicely to problem of estimating risk premiums, as there are vast amounts of financial data readily available, and numerous predictors that can be fed into a machine learning model.

Much of the literature investigating machine learning for investment valuation has focused on estimating stock returns or picking stock outperformers. As far back as 1993, Kryzanowsi et al showed how a simple neural network trained on company fundamental data and macroeconomic data can perform well when selecting stocks that will outperform (Kryzanowski, Galler and Wright, 1993). More recently, machine learning has been applied to the problem of valuation and determining equity risk premiums (i.e. the risk premiums on stocks/shares). Gu et al. found that machine learning models significantly outperformed traditional ordinary least squares regression models in estimating equity risk premiums using a large number of fundamental valuation metrics (Gu, Kelly and Xiu, 2018). They attributed this outperformance to the machine learning models ability to handle nonlinearities and interactions between the predictive variables. Comparatively little research has been conducted in the application of machine learning corporate bond realm.

This study seeks to expand upon the work of Gu, Kelly and Xiu in empirical asset valuation, except with a focus on corporate bond risk premiums rather than equity risk premiums. A deep learning model will be trained using fundamental valuation metrics such as corporate leverage and solvency ratios, individual bond terms and conditions, and observable market data including yields on short-term and long-term treasury bonds. The goal of this study is to assess how well machine learning models can predict risk premiums on corporate bonds as measured using the Option Adjusted Spread (OAS), or z-spreads for vanilla corporate bonds. The OAS was selected for the purpose of this study because it is a widely observable measure of the credit, liquidity and payment timing risk of a bond, and the calculation of OAS ensures that it is adjusted to remove potentially distorting effects of embedded options in corporate bonds, allowing for a more accurate comparison of risk and return between different bonds (Babbel and Zenios, 1992). The application of a machine learning model to estimate credit spreads on corporate bonds could be useful for asset managers for two reasons: First, if the model is found to be accurate in estimating appropriate risk premiums, it could potentially be applied to assess relative value, and to identify overpriced or underpriced bonds in the market. Second, it can serve as a tool to assess new bond issues that do not yet have observable market prices.

Much of the research in estimating credit risk employs market focused unsystematic risk variables such as the volatility of a bond issuer’s stock price, with many derivatives of this methodology referred eponymously referred to as Merton Models (Merton, 1973). However, many bond issuers are private corporations that do not have publicly listed stocks and therefore no stock price volatility to measure. This means the models cannot be applied to a large amount of the outstanding universe of corporate bonds. This research attempts to create a model that is applicable to the entire universe of outstanding bonds, focussing solely on systematic market risk measures such as general market volatility or interest rates.

## 1.2 Structure:

The structure of this dissertation is as follows…

# 2.1 Literature Review

The topic of this dissertation intersects the fields of financial economics and computer science, specifically machine learning. This review will investigate the literature around credit risk premiums, how they are estimated and how they are measured. Then it will delve into the topic of machine learning in financial applications and the state of the art around machine learning in credit analysis.

## 2.2 Credit Analysis and Predicting Bankruptcy

Arguably the first published investigation into the factors that contribute to bond risk premiums began with the seminal work of Lawrence Fisher (Fisher, 1959), who postulated that bond risk premiums, as measured by the yield on a bond less the yield on the pure rate of interest, depends on whether the firm will default and the bond marketability, and that this risk premium can be estimated using a multiple linear regression (ordinary least squares) of the logarithm of four variables: 1. The variance of the firm’s earnings over 9 years. 2. the length of time the firm has been operating without any default. 3. the market value of the firm’s equity relative to the size of its debt. 4. The market value of all publicly traded bonds the firm has outstanding, which fisher uses as a proxy for marketability. Fisher found that this model accounted for 81% of the variance in the log of risk premiums.

William Beaver posited that the use of accounting ratios could be useful as predictors of firm failure (Beaver, 1966). Accounting ratios standardise the financial results of companies, allowing for performance comparisons to be made. To test this hypothesis, Beaver took a sample of failed and non-failed firms from the Moody’s Industrial Manual, matching the, and split them by their industry type using Standard Industry Classification (SIC) codes and asset size as measured form their most recent financial statement before failure. The data was aligned to ensure failed and non-failed firms were in each industry and were similar in asset size, in a pairwise fashion. Beaver assessed 30 financial ratios related to firm cashflow, net income, debt levels, liquidity and inventory turnover, and selected one from each: Cash Flow to Total Debt, Net Income to Total Assets, Total Debt to Total Assets, Working Capital to Total Assets, Current Ratio and No Credit Interval. Through comparisons of these ratios between failed and non-failed firms, Beaver identified clear patterns which could be used as predictors of firm failure.

Edward Altman formalised the use of financial ratios for credit risk assessment using Multiple Discriminant Analysis (MDA) in what is now eponymously known as the Altman Z-Score (Altman, 1968). Similar to Beaver’s research design, Altman took a split of failed and non-failed firms. Altman assessed 22 financial ratios using correlation analysis to weed out ratios that did not add additional information to the model. Altman landed on a selection of 5 ratios: Working Capital / Total Assets, Retained Earnings / Total Assets, EBIT / Total Assets, Market Value of Equity / Book Value of Total Debt, Sales / Total Assets. Altman’s MDA model correctly classified 95 percent of the total initial sample of 33 firms, however model’s predictive capability decrease significantly as the time to bankruptcy increases. Edward Deakin combined Altman and Beaver’s models using an MDA model applied to Beaver’s set of financial ratios and achieved high predictive capability over longer time to bankruptcy measures by calculating the discriminant analysis in each of the five years to bankruptcy (Deakin, 1972).

James Ohlson extended the research, both by using much larger sample sizes than his predecessors, 2163 firms, and by employing logistic regression which gives a probability of firm failure as opposed to the binary outcome of MDA. It’s worth noting here that the logistic regression function is mathematically equivalent to the sigmoid activation function in a feedforward neural network machine-learning model. Ohlson finds that the statistically significant factors that can be used to determine probability of failure are : Firm size, measured as total assets / GNP price-level index (i.e. adjusted for inflation), Total Liabilities / Total Assets, OENEG which is a dummy variable that =1 if total liabilities exceeds total assets and zero otherwise, Net income / Total Assets, Funds from operations / total liabilities, Change in net income measures as NIt0 – NIt-1 / ABS( NIt0 ) + ABS( NIt-1 )

Zmijewski added to the accountancy based probabilistic models of bankruptcy by addressing some of the potential biases in bankruptcy data sets and by introducing a model based on the probit function. Using all listed companies on the NYSE from 1972-78, totalling in the thousands. The model results in a score that classifies firms above 0.5 as bankrupt and vice versa. The accuracy of his model was measured at above 95%.

Wu, Gaunt, Grey (2010) compare various bankruptcy probability models: Altman’s MDA method, Ohlson’s Logit method, Zmijewski’s Probit model, as well as the Shumway Hazard model and A model based on Black-Scholes option pricing. The research indicates that the Altman MDA model did not perform as well as the Probit and Logit models which in turn worked well on older data sets but not as well on more modern data sets. The Hazard model had a higher predictive capability than the others and this was attributed to its use of non-systematic market data (i.e. the company share price). As noted earlier, this type of model is only useful for companies with shares listed on the stock market, and therefor is out of scope for the research conducted in this dissertation. The same is true for Black-Scholes models. Wu et al. also construct a new model consisting of key elements from the other 5 models assessed and find it has a higher predictive capability.

While it has generally been considered axiomatic that investors will demand a premium on bonds that increases with risk of bankruptcy, a model for determining whether the bond risk premium actually exists or not was only proposed in 1999 (Elton, Gruber, Agarwal, Mann, 1999). They hypothesized that the risk premium (i.e. the ‘credit spread’) could be related to different tax treatment or other non-risk related variables. The model worked by calculating spot rates across corporate bond spot curve, effectively the yields at various cashflow payments on a bond. The model then priced the bond on a risk-neutral model. By additively factoring tax and liquidity differentials, any remaining differential can only be explained by a risk premium. The result is that they found a substantial risk premium exists in corporate bonds.

Much of the literature investigating credit spreads looks broadly at economic factors that impact general (i.e. systematic) levels of spreads for specific credit ratings categories. Andrew Davies found that credit spreads on AAA and BAA Moody’s rated bonds were positively correlated to the S&P 500 index. (Davies, 2008). Davies also found credit spreads are inversely related to the the risk-free rate, however this result is considered more controversial (See Li, X.-L., Li, X., and Si, D.-K., 2020 for a summary of contradicting evidence toward this). Another finding from Davie’s econometric model was that differing inflation regimes impacted high grade and low-grade credit in differing ways, with the latter more affected by high inflation regimes. Similarly, spreads are found to be inversely related to periods on economic expansion and periods of economic recession (Kao, 2000). Employing the multifactor vasicek model, Bhar (2010) finds that the systematic variability in US credit spreads can be mostly explained by 3 factors: 1. the stock market volatility as measured by the volatility index (VIX), 2. the stock market return as measured by the S&P 500 index, and 3. the so called ‘long bond rate’ i.e. the yield to maturity on the 10 year benchmark government bond.

In summary, there are numerous firm-level and macroeconomic variables that are relevant to bond risk premiums and corporate bond valuation. However, to the best of my knowledge, there is not a single valuation model that combines all these variables together to give a single estimate for a corporate bond. This dissertation will investigate the use machine learning against a broad set of firm-level and macroeconomic variables to gauge the capability of these models in credit valuation.

## 2.3 Machine learning applications to financial analysis

A great deal of research has been conducted in the field of machine learning applications to financial problems. This is unsurprising given financial analysis and machine learning are both data-driven processes. The majority of the research focuses on stock market prediction and trading. For a review of the literature in this field see Henrique, Sobreiro, Kimura (2019). To a lesser extent, machine learning applications to financial analysis have investigated foreign exchange rate prediction, commodity price prediction, macroeconomic prediction, portfolio management and credit risk. For a summary of the literature in these fields of research see Huang, Chai, Cho (2020).

Investigations into the use of artificial neural networks for stock selection can be traced back to the early nineties when Wong et. al. used a set of 32 company financial variables whilst applying a layer of rules based ‘expert knowledge’ (i.e. an ‘expert system’) to the data (Wong, Wang, Goh, 1992). After the expert rules were applied, the data was into an artificial neural network for predictions about stock prices for 24 stocks. Their model was highly accurate in predicting the direction of stock price movement, and to a lesser extent, the actual percent performance. The name they gave to their model was FuzzNet for fuzzy network.

Swales and Yoon (1992) compared the performance of multiple discriminant analysis (MDA) to that of an artificial neural network (ANN) to two samples of 58 companies and 40 companies from Fortune 500 and BusinessWeek respectively. For each group, the study analysed the content of the president’s letter to shareholders identifying themes of economic importance. The researchers used the frequency of theme and the percentage of the letter that was dedicated to the theme to feed both their MDA and ANN to produce a binary output of ‘good’ vs ‘bad’ as relates to the company share price performance. The ANN model without any hidden layers underperformed the MDA model at about a 52% success rate, but with additional hidden layers it outperformed the MDA model, with a 77% success rate compared to 65% success rate. They concluded that non-linear relationships between predictors were contributing valuable information to the model.

Kryanowski et. al. (1993) applied an ANN to predict stock prices returns on companies on 120 companies over a five year period from 1984-89. They trained the model on the stock return 1 year in the future, using their most recent 4 years trailing financial data, calculating ratios similar to Altman and Deakin, and trained on a set of seven macroeconomic indicators which include : Industrial production, gross domestic product, the McLeod Young Weir corporate long bond index, the 90 day treasury bill rate, the government of Canada long bond index, the consumer price index and the Montreal Exchange 25 index. Due to the small sample size, they directly encoded feature data into the model, rather than attempting to get the model to generalize the features. To do this, they encoded 3-bit combinations which translated to trends in the data, up-trend, down-trend or stable. Their tests achieved a 66.4% overall accuracy in predicting whether a stock’s return would be positive or negative in the following year.

More recently, Gu et. al. (2018) compared the success of various machine learning algorithms against a large universe of stocks and predictors to measure equity risk premiums. Their sample included nearly 30,000 individual stocks over a 60 year period, employing over 900 variables based on 94 predictors for each stock, 8 predictors calculated as interactions with the 94 independent variables, as well as 74 dummy variables reflecting industry sector. Employing such a large set of independent variables is novel to the economic literature which largely focuses on linear models which cannot consume so many inputs. The research is also novel in that they investigate and compare which predictors are most influential amongst the different models employed. They find the models are mostly in agreement about the set of predictors found to be the strongest. This adds to the robustness of the findings. Finally, they demonstrate significant economic gain in the use of machine learning algorithm as compared to liner models in stock selection.

While all of the above focus on investment valuation in equity markets, relatively less research has investigated machine learning applications in the bond market.

Bianchi , Buchner, Temoni (2019) investigated boosted regression trees, random forests, extremely random randomized regression trees and shallow and deep neural networks to predict bond risk premiums focusing narrowly on the treasury market, first by using yield curves as predictors, and then by adding several time series of macroeconomic variables to the model. They found neural networks performed well in the yield-only case, and even better when employing macroeconomic variables. The following macroeconomic variables were studied: real output and income, employment and hours, real retail, manufacturing and sales data, international trade, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labour costs, capacity utilisation, price indices, interest rates and rates spreads, stock market indicators and foreign exchange rates.

Credit ratings are an area where machine learning has enjoyed a significant amount of focus and success. This not surprising given the categorical nature of credit rating, it’s a problem well suited to machine algorithms. For a review of the literature in this field, see Golbayani, Florescu and Chatterjee (2020). Golbayani et. al. also contributed to the literature with comparative study, employing bagged decision trees, support vector machines and multilayer perceptrons, and finding the decision trees had the best performance.

Credit spreads (i.e. risk premiums on corporate bonds) are an area that has received little attention in the field of machine learning. Kim, Kim and Jung (2021) compared various machine learning methods against linear regression models to predict the 1 year and 2 year corporate bond yield spreads. Yields were calculated by taking the volume-weighted average price of trades from the American TRACE reporting system. The independent variables they chose were : credit ratings, interest rate volatility, equity index volatility, bond maturity and coupon rate, and liquidity (measured as number of days bond traded in past 12 months). The models they employed were Ridge, multivariate adaptive regression splines, neural networks, random forest and support vector machines. They found neural networks to outperform all other methods.

7Liu, Zhou and Xiong (2021) proposed a novel depth-gated recurrent neural network with a self-attention mechanism for the prediction of credit spreads. Their research investigated the Long-Short-Term meory (LSTM) neural network architecture, the Gated Recurrent Unit (GRU) Neural Network architecture, and the Just Another NETwork (JANET) neural network architecture compared against linear models. They also implemented a Self-Attention mechanism that dynamically generates weights for different connections within neural network layers. Adaptive Momentum Estimation (Adam) optimizer and Extreme Gradient boosting (XGBoost) were employed for training, and the mean squared errors was selected as a loss function. Predictors included the Risk Free interest rate, credit spread term structure, stock index return, stock index volatility, exchange rates, Oil Prices, TED Spread, swap spread and the commodity price index. Credit Spreads in this strudy were taken on aggregate by using ICE BofAML credit indices. Their findinds findings suggest the self-attention mechanism can improve results in neural network architectures.

(note all seem to use nominal spread which is not great)

**Project Objectives**

A potential limitation of using the OAS were raised by Babbel and Zenios. The OAS is model dependent, it relies on the assumption that the pricing model for the bond is accurate. Because bonds are infrequently traded, much of the bond price data in the market is based on a modelled price, called ‘Matrix’ pricing, rather than an observed market price. As the OAS is calculated from the bond price, this may mean that bias in the pricing model introduces bias into the OAS. Despite this limitation, the OAS is the most accurate measure for bond risk premiums available and is widely used in the market. (RENE Model can learn matrix model instead – try to get real tradeprices)

Care must be taken in the construction of this study to avoid common pitfalls. Buczynski et al. observed that while a large amount of published experimental research claim to achieve highly profitable investment strategies employing artificial intelligence, there is a conspicuous absence of success in the marketplace. They investigated 27 academic experiments and found major shortcomings such as running many models over the data and then ‘Cherry Picking’ the successful models, as well as a reliance on poor measures of success such as mean error (Buczynski, Cuzzolin and Sahakian, 2021). Furthermore, the statistical significance of the results of many studies in the field of financial economics is often found to be exaggerated, (Harvey, 2021). In an effort to avoid the overfit issue common in ML projects, this study proposes to use new bond issues as an out-of-sample test. To avoid the criticism of cherry-picking results, this study will employ a single feed-forward neural network model consisting of 3 hidden layers. This set up is consistent with the outperforming neural network model employed by Gu, Kelly and Xiu. They attributed the outperformance of the relatively shallow neural network to the low noise-to-signal ratio and small datasets employed when working with financial data.

Gu, Kelly and Xiu performed their equity risk premium study on 30,000 stocks over the 60 years ranging from 1957 to 2016. Through a detailed survey of literature regarding factors impacting equity valuations, they selected and employed a set of 94 investment characteristics and 8 macroeconomic variables as model predictors, as well as 74 industry sector dummy variables. This represents a massive number of predictors as compared to traditional economic models for investment valuation. The ability for machine learning models to consume such a large number of predictors is novel in the field of financial economics and is something this study hopes to replicate. Ideally, this study would aim to be equally ambitious in terms of quantity of data used to train the model. However, it is unlikely there will be corporate bond OAS data going very far back, given the computationally demanding nature of calculating OAS. Furthermore, the universe of corporate bonds is much larger and more diverse than equities while being less liquid, meaning the data available is likely to be of lower quality. Finally, it is reasonable to assume that a much smaller set of company financial variables will impact valuations on debt because the value of debt is not linked to future earnings growth in the same way that equity is. Debt valuations will be limited specifically to financial variables that impact the corporation’s ability to service its debt. All these factors contribute to a relatively smaller set of model predictors. Table 1 below presents an initial set of relatively common credit risk predictors that this study will consider for inclusion. The literature review phase will include an economic research portion dedicated to reviewing potential inclusions or deletions from this list informed by peer reviewed research.

|  |  |  |
| --- | --- | --- |
| **Bond Characteristics** | **Company Data** | **Market Data** |
| Time to Maturity (yrs) | Debt/Capital Ratio | Yield on 3-month Treasury |
| Liquidity | Debt/EBITDA Ratio | Yield on 1-year Treasury |
| Senior/Subordinated | FFO/Debt Ratio | Yield on 3-year Treasury |
| Restrictive Covenants | EBITDA Margin | Yield on 5-year Treasury |
| Coupon | Return on Capital | Yield on 10-year Treasury |
| Coupon Frequency | EBIDTA/Interest Expense | Inflation Rate |
|  | Enterprise Value |  |
|  | Company Sector |  |

Table 1 – Suggested Model Predictors

Once the model is trained, robustness will be tested by looking at the OAS predicted by the model compared to OAS observed in the market. The mean error and variance will be the basic measures of accuracy for the model, along with distribution of error which should address some of the criticisms raised by Buczynski et al.. Furthermore, the differences in observed versus predicted OAS will be broken into deciles. The bonds landing in the top and bottom deciles will be observed over a period of 3 months to see if the market OAS converges toward the predicted OAS. Convergence would suggest there exists utility in using machine learning to identify overvalued and undervalued bonds. Finally, following similar lines of investigation as Gu et al., the neural network weightings will be observed and ranked to give insight into which predictors are found to be most beneficial in predicting the OAS.

**Resource Requirements and Risks**

The major resource requirement for this project is data. Sourcing quality data will likely be challenging. Two potential data sources available from the University of Bath Library are : S&P Capital IQ Pro and Refinitiv Datastream/Eikon. If these resources are insufficient, two other potential options are FactSet and Bloomberg, however access to these data sources will need to be organised privately as they are not available through the University Library. Prediction accuracy in machine learning increases when training on increasingly large data sets. Furthermore, economic studies are most representative when they include data from the entire economic cycle and from various economic environments. Therefore, it would be ideal if corporate bond OAS data can be sourced as far back as the highly inflationary period of the 1970s, because inflation is factored into bond risk premiums. However, as previous mentioned, calculating OAS is computationally demanding, so it is possible that this data was not produced that far back in time. Taking inspiration form Gu et al., this study will seek 30000 bonds across 76 industry sectors with observations taken quarterly or semi-annually as available based on accounting data, going back as far in time as possible. However, this scope is dependent on the ease in which the data can be obtained and may shrink considerably if the data is difficult to access.

Another major challenge relates to data timing and look-ahead bias. Markets rapidly adjust to new information such as company financial disclosures (Fama 1970). Therefore, it will be important to ensure that the bond OAS data is collected in such a way that its timing corresponds closely to the release of the company financial data that is fed into the model. This may be more complex than it sounds since because financial databases may not be designed to ensure financial data is presented exactly on the date it was released to the market. However, there may be some flexibility for timing given that the model is estimating the size of the risk premiums rather than predicting investment returns.

A separate resource requirement is computation and storage. A data-size estimate was created by assuming 30,000 bonds, the 20 predictors from Table 1 and a single OAS value. The estimate was created by filling a CSV file measuring 30,000x21 cells all containing 7-digit numbers. The file size was just below 5 MB. If quarterly observations can be obtained from 1970 to 2020, that would mean 200 observations. This equates to a gigabyte of data which is not highly resource intensive. Computational requirements will be outsourced to a cloud provider such as Google Collab. Software resources will be very low, relying on open-source machine learning solutions such as Tensorflow/Keras.

The main risk for this project is sourcing data. It is possible that I will not be possible to source the large data set envisaged for this project, particularly if data providers cannot provide this in bulk. To be realistic, some flexibility to reduce the scope of the project must exist if the data collection turns out to be more challenging than expected. Also, some flexibility around project outcomes could serve as a contingency. For example, rather than trying to predict credit spreads, the project could be modified to try to predict credit ratings upgrades and downgrades which are also valuable to investors for the purpose of valuation.

Timeline

Description automatically generated

Figure 1 – Project Timeline

# GLOSSARY OF FINACIAL TERMS

**Asset**: Here used as a synonym for an investment

**Asset Valuation**: Specifying the percent return an investment should provide an investor in order to compensate for the perceived risks of holding that investment.

**Credit**: Here used as a synonym for corporate bond

**Credit Spread**: The difference in yield between a risky bond and a risk free government bond of equal maturity and currency

**EBIT**: Earnings before interest and taxes. A measure of business profitability before costs of servicing debt and taxes.

**EBIDTA**: Earnings before interest, depreciation, taxes, and amortization. A measure of business profitability before costs of servicing debt and taxes, and prior to some of the potential distortions of modern accounting methods.

**Enterprise Value**: The sum of the market value of a company’s debt and equity. Viewed as the total value of a business, or the cost of purchasing an entire business and therefore taking ownership of the company’s debt obligations.

**FFO**: Funds from operations. This represents the cash a business generates from conducting its primary business operations

**Fundamental Valuation**: Analysing financial health of a company to arrive at a valuation for the investments they issue.

**Liquidity**: The ease with which an investor can sell (liquidate) an investment.

**Leverage**: The amount of debt a company holds

**Maturity**: The expected date a bond will be repaid to investors

**Options**: A financial instrument or a feature of a bond that allows the holder to buy or sell an investment at a given price in the future.

**Option Adjusted Spread (OAS)**: A single discount rate added to each point of the risk-free term structure, which when used to discount a risky bond’s cash flows, makes the discounted cash flows equal to the observed market price of the bond after adjusting the price for any embedded options. The OAS can be viewed as a measure of a bond’s credit spread, however it also includes other risks such as liquidity risks. In the absence of embedded options, the OAS is equivalent to the Z-Spread.

**Risk Premium**: The percent amount an investment will compensate an investor as compared to a risk free investment.

**Solvency**: The risk a company will not be able to repay its debts

**Systematic Risk**: Risk variables that that impact the entire universe of an investment and therefore are inherent to the entire market

**Unsystematic Risk**: Risk that is specific to an individual investment or firm.

**Vanilla Bonds:** Bonds that contain no special price features suck as sinking funds or embedded options

**Yield**: Short for Yield-to-Maturity which is the expected return a bond should provide an investor if held to the maturity date of the bond.

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