Determining Lessee Discount Rates for Lease Measurement under ASC 842

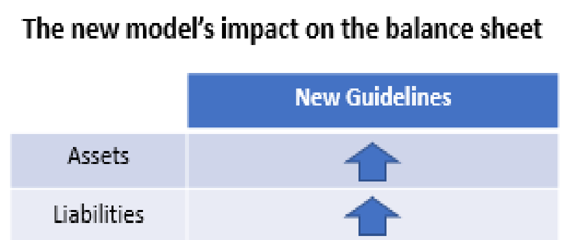
Introduction and Overview

LeaseSCRE Overview

Alvarez & Marsal ("A&M") developed a web-based tool, LeaseSCRE (pronounced "lease score"), to assist companies in determining their incremental borrowing rate ("IBR"). LeaseSCRE estimates a company's incremental borrowing rate as required under the ASC 842. The process involves estimating what S&P would rate a company's credit using A&M's Sample Credit Rating Estimator ("SCRE"), mapping the estimated credit rating to a Credit Default Swap ("CDS") curve and adjusting the curve for collateralization. The result is an IBR that can be used to discount lease payments based on the tenor of the lease and the company's creditworthiness. This paper will introduce the lease accounting standard, describe SCRE, and support our use of CDS curves and the adjustments for a collateralized borrowing rate curve.

Introduction to the Lease Accounting Standards (ASC 842)

The FASB new lease accounting standards, ASC 842, replaces the current guidance, ASC 840, effective December 15, 2018. The new standards introduce changes to how companies are required to account for operating leases on the balance sheet. In the past, companies capitalized their financing leases while operating leases were disclosed in the footnotes. However, to increase transparency into the financial standing of companies, FASB created ASC 842 so that right-of-use assets and lease liabilities for all operating leases longer than 12 months are recorded on the balance sheet. The standards define operating leases as any lease other than a finance lease[1]. While the new standards clearly communicate the required changes for lease accounting, companies will find that gathering the necessary inputs required to comply with the new standards can be challenging.



Most companies will recognize a significant increase in the overall number of leases recorded on their balance sheets, increasing the total value of their assets and liabilities.

The lease liability generated from an operating lease is calculated by finding the present value of future lease payments at a discount rate which complies with the new standards. Once the lease liability is determined, it serves as a starting point for determining the right-of-use asset. In order to record the right-of-use asset, companies will start with the lease liability and adjust for payments made prior to the lease commencement date, lease incentives offered to the lessor, and initial indirect costs to arrive at the asset value. Sourcing accurate inputs, namely the discount rate, will be important for companies to properly perform a present value calculation of their lease liability.

[1] Source: Financial Accounting Series, No. 2016-02 (https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1176167901010&acceptedDisclaimer=true)

A lessee could ascertain the implied discount rate from the lease contract, if the lessee was provided certain information by the lessor. This information includes the fair value of the underlying leased asset, the estimated residual value of the leased asset, and any initial indirect costs incurred by the lessor. These calculation inputs are rarely available to the lessee to determine an implied discount rate.

Recognizing this issue, ASC 842 recommends that companies use their incremental borrowing rate (IBR). The guidelines define the IBR as:

"the rate of interest that a lessee would have to pay to borrow on a collateralized basis over a similar term an amount equal to the lease payments in a similar economic environment.[2]"

Companies may be unaware of their IBR if they do not borrow on a collateralized basis. While some companies borrow on a collateralized basis, using the collateralized rate as the discount rate for discounting lease payments may present issues as the collateral used for the loan may vary in nature from the leased assets, making the rates incomparable. Additionally, the loan terms, including size, payment structure, and tenor, may vary from the lease terms.

Our Methodology

Lessees can arrive at their IBR by following a three-step approach that relies on a systematic, data-driven process.

Step1: Estimate what Standard & Poor's might rate the lessee's credit

Step 2: Derive an unadjusted unsecured borrowing rate using the estimated credit rating and lease tenor

Step 3: Adjust the rate to reflect borrowing on collateralized basis

Using this method, companies can obtain a rate to discount their lease payments and to record their lease liabilities that is specific to their estimated credit rating. The rate provided may require adjustments for various factors such as company specific factors or leased asset specific factors. The next section will discuss the first step in the process, estimating what S&P might rate a company's credit.

Step 1: Estimate what Standard & Poor's might rate the lessee's credit

Credit Ratings and Methodology

Corporate creditworthiness is one of the most substantial variables to assess collateralized incremental borrowing rates. Lenders will require higher rates of return when lending to financially insecure companies than lending to financially stable companies.

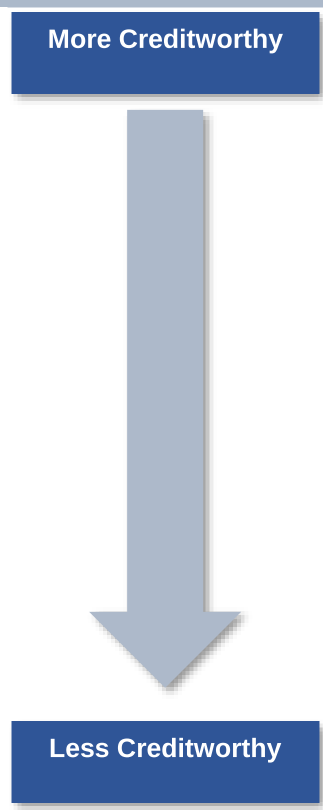
The classification of corporate creditworthiness is commonly done through the application of corporate credit ratings, which are issued by Credit Rating Agencies such as S&P, Moody's, and Fitch. These ratings

[2] Source: Financial Accounting Series, No. 2016-02 (https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1176167901010&acceptedDisclaimer=true)

provide a consistent approach to determine a company's ability to repay its obligations across industries.

When determining a corporate credit rating, ratings agencies will assess a company's ability to meet its outstanding obligations. Specifically, they will assess the company's financial information, outstanding obligations, ability to borrow, payment track record, operational performance, short, medium and long term plan, exposure to industry, economic and systemic risks as well as any intangible factors that may impact the company. The concluded credit ratings are expressed differently based on rating agency but they fall into the same categories as shown in the chart below:

Moody's	S&P	Fitch
Aaa	AAA	AAA
Aa1	AA+	AA+
Aa2	AA	AA
Aa3	AA-	AA-
A1	A+	A+
A2	A	A
A3	A-	A-
Baa1	BBB+	BBB+
Baa2	BBB	BBB
Baa3	BBB-	BBB-
Ba1	BB+	BB+
Ba2	BB	BB
Ba3	BB-	BB-
B1	B+	B+
B2	B	B
B3	B-	B-
Caa1	CCC+	
Caa2	CCC	CCC
Caa3	CCC-	



According to this criteria, AAA companies are viewed as the most creditworthy, BBB rated companies are determined to have adequate capacity to meet their financial obligations, while CCC rated companies are determined to be currently at risk of not meeting their financial obligations.

On a population-wide basis, these assessments have produced results in line with their stated purpose. According to S&P and as shown in the table below, default rates have been significantly higher for lower-rated companies[3].

[3] Source: S&P Global's 2017 Annual Global Corporate Default Study and Ratings Transitions *(https://www.spratings.com/documents/20184/774196/2017+Annual+Global+Corporate+Default+Study)*

Descriptive Statistics On One-Year Global Default Rates

	AAA	AA	A	BBB	BB	B	CCC/C
Minimum	0.00	0.00	0.00	0.00	0.00	0.25	0.00
Maximum	0.00	0.38	0.39	1.01	4.22	13.84	49.46
Weighted long-term average	0.00	0.02	0.06	0.17	0.68	3.59	26.82
Median	0.00	0.00	0.00	0.07	0.58	3.41	24.50
Standard deviation	0.00	0.07	0.10	0.26	1.01	3.29	11.61
2008 default rate	0.00	0.38	0.39	0.49	0.81	4.09	27.27
Latest four quarters (Q1 2017-Q4 2017)	0.00	0.00	0.00	0.00	0.08	0.98	26.23
Difference between past four quarters and weighted average	0.00	(0.02)	(0.06)	(0.17)	(0.61)	(2.61)	(0.59)
Number of standard deviations	0.00	(0.29)	(0.57)	(0.67)	(0.60)	(0.79)	(0.05)

Sources: S&P Global Fixed Income Research and S&P Global Market Intelligence's CreditPro®.

While credit ratings help the market assess and categorize credit risk, they require extensive analysis and can place high costs on companies seeking them. According to S&P, corporate bond credit ratings carry a minimum fee of $100,000 and are 6.95 basis points of any transaction value for most transactions[4]. As such, obtaining full credit ratings from ratings agencies can be time consuming and financially burdensome for many companies.

Alternative Methodologies for Credit Rating Estimation

Given the usefulness of credit ratings to many business functions, numerous alternatives to full credit rating analyses have been developed.

Significantly, major ratings agencies began issuing "Shadow Ratings" which represented non-public ratings analysis which were less expensive and were generally understood by market participants to be accurate within "two notches" (i.e. a B+ shadow rated bond could fall between B- and BB in a full ratings analysis).

While the lower cost of shadow ratings enabled the use of shadow ratings in certain contexts, such as smaller debt transactions, the cost was still prohibitively expensive and lacked the underlying support and documentation for use in many contexts. After the financial crisis, ratings agencies began to curtail their issuance of shadow ratings due to their ongoing questions about methodology, process and accuracy.[5]

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[4] Source: S&P Global Ratings U.S. Ratings Fees Disclosure *(https://www.standardandpoors.com/en_US/delegate/getPDF;jsessionid=A53F3E0088247DD274D992FC09076FC6?articleId=2148688&type=COMMENTS&subType=REGULATORY)*

[5] Source: Alloway, Tracey (2011, July 5). Shadow ratings go dark at S&P. *The Financial Times (https://ftalphaville.ft.com/2011/07/05/613206/shadow-ratings-go-dark-at-sp/)*

In the absence of a formal analysis from ratings agencies, analysts often apply linear models, financial ratios analyses, or a combination of the two.

In 2006, Moody's Investor Services published "Moody's Credit Rating Prediction Model"[6] a lineal model which claimed 89% accuracy within "two notches." While accurate, the model required five years of historical company financial data and overall industry financial data, making implementation challenging. At present Moody's does not appear to have issued an update to the model, creating potential issues regarding the model's applicability to present market circumstances.

Other popular linear models such the one put forth by Minardi et. al.[7] often attempt to rate companies on a "full rating" basis, that is ignoring +/- "notching" (i.e. both BBB+ and BBB- rated companies are considered BBB). These models tend to claim high levels of accuracy within a full rating. For instance, Minardi et. al. claim 96.7% accuracy within a full rating.

However, as shown in the chart below, this implies that a company with a BBB rating indication can have actual ratings that range from A+ to BB- or four "notches" in either direction. Given that these algorithms generally consider ratings from AAA to CCC, the range which is considered "accurate" encompasses 43% of available ratings. As with Moody's Credit Rating Prediction Model, publication of updates to these models can be sporadic.

"Full" Ratings		"Notched" ratings	
AAA		AAA	
		AA+	
AA		AA	
		AA-	
		A+	
A		A	
		A-	
		BBB+	
BBB	Range of possible "accurate" outcomes for a BBB "Full" rating prediction	**BBB**	Range of possible "accurate" outcomes for a BBB "notched" rating prediction
		BBB-	
		BB+	
BB		BB	
		BB-	
		B+	
B		B	
		B-	
		CCC+	
CCC		CCC	
		CCC-	

In the absence of linear models, analysts often turn to financial ratio analysis. One common source for these ratios is S&P's *Adjusted Key U.S. And European Industrial And Utility Financial Ratios* reports, which laid out ratios in tables like the one below.[8]

[6] Metz, Albert; Cantor, Richard. (November 2006). Moody's Credit Rating Prediction Model. *(https://www.moodys.com/sites/products/DefaultResearch/2006200000425644.pdf)*

[7] Minardi, Andrea; Sanvicente, Antonio Zoratto; Artes, Rinaldo. A Methodology for Estimating Credit Ratings and the Cost of Debt for Business Units and Privately held Companies. *(https://crc.business-school.ed.ac.uk/wp-content/uploads/sites/55/2017/03/minardi-andrea-estimating-credit-rating.pdf)*

[8] Fielding, James. (2014, August 29). 2013 Adjusted Key U.S. And European Industrial And Utility Financial Ratios *(http://www.alacrastore.com/s-and-p-credit-research/CreditStats-2013-Adjusted-Key-U-S-And-European-Industrial-And-Utility-Financial-Ratios-1356447)*

Adjusted Key Industrial Financial Ratios, Long-Term Debt--U.S.						
Medians of three-year (2011 to 2013) averages						
	AAA	**AA**	**A**	**BBB**	**BB**	**B**
Oper. income (bef. D&A)/revenues (%)	28.0	26.9	22.7	21.3	17.9	19.2
Return on capital (%)	30.6	21.6	22.2	14.2	11.1	7.1
EBIT interest coverage (x)	40.8	17.3	10.3	5.5	3.2	1.3
EBITDA interest coverage (x)	48.3	21.3	14.1	8.2	5.2	2.8
FFO/debt (%)	293.8	117.3	68.6	35.4	24.4	12.0
Free oper. cash flow/debt (%)	189.0	78.8	45.9	19.4	11.5	3.5
Disc. cash flow/debt (%)	92.6	48.0	30.5	13.3	8.4	2.2
Debt/EBITDA (x)	0.1	0.5	1.0	2.0	2.9	4.9
Debt/debt plus equity (%)	2.8	17.2	30.7	41.1	50.4	72.7
No. of companies	4	15	94	233	253	266

However, S&P stopped issuing reports on these statistics after 2013, meaning that most officially sourced data is outdated. Analysts can also tabulate median ratios by rating using updated market data to fill out tables like the one above.

Regardless of data quality, ratio analysis has a severe limited ability to predict ratings. One of the most common metrics used in ratio analyses is Debt/EBITDA. Using a table like the one above, an analyst would get the impression that a Debt/EBITDA of 2.9x implies a BB rating. However, a 2.9x Debt/EBITDA ratio falls in the middle 50% of observations for every rating from A to B+ (e.g. 2.9x is encompassed within the range from the 25th percentile to the 75th percentile of all observations for each rating). This means that a Debt/EBITDA of 2.9x can support rating conclusions ranging from “strong capacity to meet its debts” to “more vulnerable to financial pressures.”

This is a common issue in financial ratio analyses. The variances within metrics are underestimated by analysts and introduce a substantial amount of subjectivity into the analysis. As a result, analyses that rely solely on traditional ratios have not been proven to be predictive without the aid of qualified and experienced professionals.

Alvarez & Marsal’s Sample Credit Rating Estimator (SCRE) Introduction

Given the shortcomings in the rating analyses described above, we examined whether a model based on machine learning techniques could improve existing ways of estimating credit ratings (Exhibit 2). Ultimately our measures for success were:

1. More accurate than observed ratings techniques
2. Delivers unbiased rating predictions
3. Inclusive of current market data
4. Ability to be implemented easily with limited data requirements

To achieve this, we developed a Machine Learning model, specifically a Random-Forest regression model (Exhibit 3), that: 1) Currently achieves greater than 92% accuracy within “two notches” on testing data; 2) Underestimates approximately 5% of ratings and overestimates approximately 4.0% of ratings; 3) Includes market data up to the most recent quarter end and; 4) Requires one-year financial statement inputs and delivers results instantly.

Data Collection

To develop the SCRE model, we used S&P Capital IQ to perform quarterly searches from March 31, 2013 to the most recent quarter end public filings for public companies that met the following criteria:

1. The company's primary location (as defined by Capital IQ) is within the United States of America
2. The company's market capitalization is above $50 million
3. The company's enterprise is above $50 million

This generated a database of over 100,000 observations. We then filtered observations using the following criteria:

1. Observations where the company's primary sector is Financials (approximately 30,000)
2. Observations where the company does not carry a rating between AA+ and CCC- (approximately 50,000 observations). Note that AAA rated observations were excluded due to limited observations (All observations were either Automatic Data Processing, Exxon Mobil, Johnson & Johnson and Microsoft)
3. Companies with LTM Assets or Revenue below $10 million (<250 companies).
4. Companies with Debt Outstanding of at least $10 million (<250 companies).

This narrowed the number of observations to approximately 25,000 to use for training and testing the Machine Learning algorithms. For each of these observations, we collected nearly 300 features that could be used in the analysis.

Data Partitioning

Given that quarterly observations are being used by the algorithms, there is a risk that similar observations will be used by both the training and testing dataset. For example, the observation for Sysco in Q3 2018 will be very similar to the observation for Sysco in Q4 2018. If a model were to train itself on data with company observations appearing in both the training and testing dataset, it would report artificially high levels of accuracy.

To guard against this risk, we partitioned company observations into either the training or testing dataset. No company's observations were in both the training and testing dataset.

Model training and testing

The partitioned data was uploaded to approximately 40 different Machine Learning algorithms to see which ones generated the most promising results (Exhibit 2). After assessing the results, we selected a "Random Forest Regressor" as the basis for our model (Exhibit 3).

Random Forest estimators rely on a combination of multiple decision tree estimators that use random subsets of training data. In our model, each individual tree predicts a credit rating which is represented by a number (e.g., one for AA+, two for AA), and the individual predictions are then combined to determine a final predicted rating[9].

Feature selection

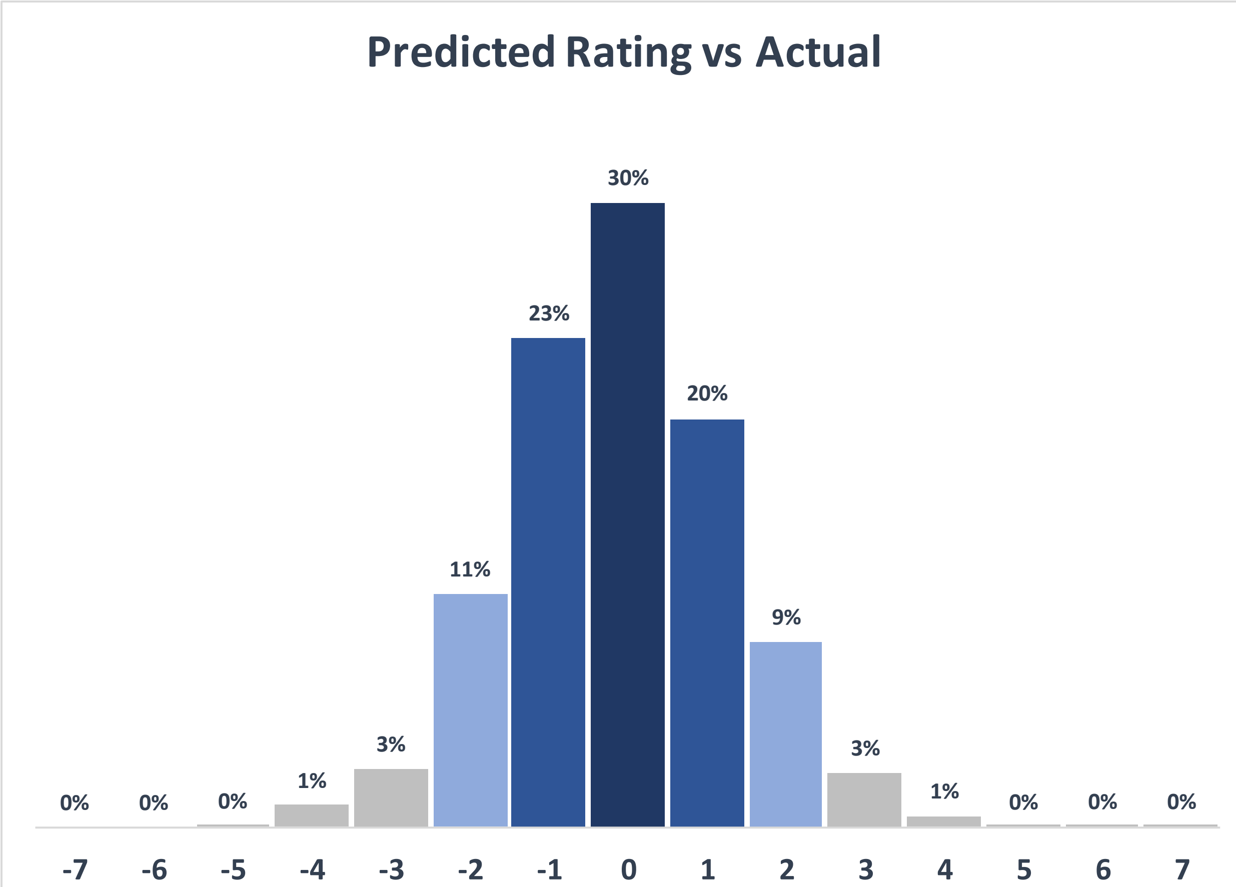
We then performed a feature selection and optimization analysis to reduce the data capture requirements associated with the analysis. In feature selection, the least predictive feature of the selected algorithm is removed, and the algorithm is re-trained. This process is repeated, and the testing accuracy is recorded until no features are remaining.

This allowed us to reduce our list of required inputs while maintaining a greater than 90% accuracy level. On an ongoing basis, the features utilized may change based on our retraining process.

Summary of results

Based on a testing sample of approximately 6,000 observations, approximately 30% of predictions were accurate to the nearest "notch" and greater than 90% of predictions were within two "notches." Error rates were similar between high and low predictions. Using financial information from current financial statements and our random forest regressor machine learning model (SCRE), we are able to estimate the Credit Rating S&P might provide to a company. These estimated ratings have a lower error rate than other published model results without bias towards higher or lower rates. The ratings are for unsecured debt obligations. In the next step, the rating will be used to estimate the borrowing rates by tenor for similar rated companies.

[9] For further details on Random Forest Regressions, please refer to: Breiman, Leo. (January 2001). Random Forests (https://www.stat.berkeley.edu/~breiman/randomforest2001.pdf)



Error rates also were similar across time periods as well as between high and low predictions.

Step 2: Derive an unadjusted unsecured borrowing rate using the estimated credit rating and lease tenor

An Overview of the CDS Curve and Methodology

The incremental borrowing rate (IBR) is a collateralized borrowing rate that factors in tenor and current economic conditions. Our process begins with determining the unsecured borrowing rate using CDS yields.

A credit default swap (CDS) is an over-the-counter contract between a buyer of protection against the risk of a company defaulting on a loan and a seller of such protection. In effect, it is an insurance policy that protects the buyer of the CDS against the loss of the loan principal if the issuer defaults on a loan because the buyer has the right to sell the bond for its face value in the event of a default.

A CDS spread is the amount that the buyer of protection pays to the seller, expressed as basis points per year of the contract's notional amount. For example, if a CDS spread is 300 basis points on a $10MM loan, then the buyer pays $300,000 per year to the seller of the protection and obtains the right to sell the bond for $10MM in the event of a default. There is a direct positive relationship between a company's probability of default and the size of the spread; the lower a company's credit rating, the larger the company's CDS spread will be. The CDS yield is calculated by adding the risk-free rate to the CDS spread. The risk-free rate used to calculate the CDS yield is the LIBOR zero curve. While many bond traders tend to consider the treasury zero curve to be the risk-free rate, derivative traders who work for large financial institutions regard the LIBOR zero curve, which is the basic rate of interest used for inter-bank lending, to be the risk-free rate because it better represents their opportunity cost of capital than the treasury zero curve. The CDS spread quantifies the creditworthiness of company, and added to the risk-free rate, offers a starting point for determining a company's borrowing rate. This yield should be equal to a bond yield as there should be no opportunity for arbitrage to buy the bond, short LIBOR and sell CDS.

The CDS yield serves as the unsecured borrowing rate since the data that is used in calculating CDS spreads is based on unsecured loans. While analyzing bond yields may provide insight into the unsecured borrowing rate, using CDS yields instead has certain advantages over using bond yields because CDS yields reflect current market rates, account for tenor, and require fewer assumptions. CDS yields represent the current economic environment because they are traded on a highly active market and represent an obligation to transact compared with bond yields, which are only an indication of interest (Exhibit 1). Since the IBR requires consideration of tenor, CDS yields offer a good option for deriving the appropriate borrowing rate. CDS yields can be plotted across tenors to create a curve, allowing for interpolation to match the lease tenor. Companies issue bonds at various times with varying terms to maturity. This leads to spotty coverage of bond yield over certain tenors. In addition, bonds have various other features and options that make estimating the yield difficult. Since CDS spreads are aa uniform product specific to default risk on obligations they are easier to derive and more consistent across companies.

CDS yields can be modeled across tenors to form a CDS yield curve. Furthermore, a curve can be created for each rating category on the S&P credit rating scale. Using the appropriate rating curve, the unsecured borrowing yield is found by matching the point along the curve with the tenor of the lease. For example, if SCRE estimates that a company's rating is AA+ and the lease tenor is 5 years, then unsecured borrowing rate would be the point along the AA+ CDS yield curve at 5 years.

At each tenor, the yield that is derived from the CDS yield curve applies to all companies within the rating category. SCRE utilizes industry as one of the features to estimate the potential S&P credit rating. S&P considers industry and sector risk factors, such as trends in industry barriers, profit margins, and competitive threats, when issuing a credit rating for a company (Exhibit 5). The unsecured borrowing rate derived from the CDS yield curve is applied to all companies in each rating and tenor.

CDS spreads are combined with LIBOR zero curve to create the CDS yield curve. The data for this is refreshed daily. CDS Yields are the average of traded CDS at each rating level. Data on the universe of actively traded CDS spreads on unsecured issues is collected for each rating category on a monthly basis. The average spread between the full rating and notched rating is calculated at various tenors. There were over 1000 observations across all rating categories. Data points that are more than two standard deviations from the mean are removed from the data set. To obtain a rating specific IBR, companies need to apply an adjustment for an IBR on a collateralized basis.

Step 3: Adjust the rate to reflect borrowing on a collateralized basis and other lease-specific factors

Overview

The new guidelines define the IBR as a rate that lessees pay to borrow on a collateralized basis. Since the CDS curves are based on unsecured loans, a collateralization adjustment is made to reflect a securitized, or collateralized, borrowing rate.

Calculating the collateralization adjustment requires knowledge of the hypothetical difference between the rate that a lender would offer to a company on a secured basis and the rate that the lender would offer to the company on an unsecured basis. These loans must be considered at the same tenor so that the difference in the rates is not affected by tenor.

While there may be different analyses that conclude upon the difference between unsecured and secured rates, the data supporting any analysis should include secured and unsecured loans at various tenors for each company.

Loan matching methodology

Loan matching is a process where each company's loans are analyzed at various tenors and a pair of loans is selected if, at that tenor, the company holds an unsecured and secured loan. The differential between the secured and unsecured loan is then calculated. There were over 2000 pairs. Of these pairs, instances where the unsecured rate was lower than the secured rate were removed. For example, in one such observation, the secured rate was 11.5% and the unsecured rate was 7.6%. Loans with collateralization offer greater security to the lender than unsecured loans and therefore should carry a lower required yield than unsecured loans. A data set of over 140 observations was used to calculate the spread between the unsecured loan and secured loan. The observation count of is statistically significant enough on which to draw conclusions about the population spread. At 140 observations, we would be 95% confident that our margin of error is within 35 basis points (Exhibit 4).

The loan matching process began with collecting loan data, sourced from Thompson Reuters, on a sample of 2,272 companies representing 47 different industries as of 1/2/2019. This data set contained 18,673 loan observations. Each observation had several important data fields associated with it, including yield-to-worst, credit rating, securitization status, tenor years, and the loan size. A maximum yield-to-worst of 30% was applied to the data set since this threshold represented a natural breaking point in the distribution of yields, eliminating values that were extreme by this definition. Tenors on loans ranged from 0 to 101 years to account for the range of possible lease terms. A minimum value of $10,000,000 was applied to the loan size to ensure that the data collected was on loans that were actively traded on the market.

The distribution of secured versus unsecured loan spreads was modeled, and several statistical measures of the distribution were considered, including the mean, median, minimum, and maximum. The median measure was selected to serve as the collateralization adjustment since there were outliers in the data that caused the average to be unrepresentative of the typical spread between an unsecured and secured loan. The data underlying this collateralization adjustment process is refreshed monthly.

The median serves as the appropriate measure to adjust the unsecured borrowing rate derived from the CDS yield curve. This is because the median better represents the central tendency of the data set due to the presence of outliers in the first and fourth quartile. This adjustment is applied to companies across ratings because there is little correlation between the size of the spread and the creditworthiness of the company (Exhibit 6). A regression analysis indicated that the relationship between the secured versus unsecured loan spread and the credit rating is very weak, with an R-square of 0.185.

Adjustment 2: Consideration for Other Lease-Specific Adjustments

LeaseSCRE provides lessees with a market-based discount rate that would apply to all companies in each rating category. However, there are certain lease specific adjustments that companies may want to make to reflect specific considerations concerning their lease obligation. For example, companies can adjust for the marketability or liquidity of the leased asset. Leased assets that are specialized in nature can make the job difficult for a lender to find a buyer for the asset if the borrower defaults. Consider a situation where a company is taking on a lease to build a custom gas compressor located near a secured military zone and another company is taking on a lease for the same amount and tenor to build a warehousing facility near a large metropolitan area. A lender would have an easier time finding a buyer for the warehouse than for the gas compressor because the warehouse is more fungible than the gas compressor. Another adjustment example is collectability. Lenders may want to charge a higher rate for assets that are less collectible, such as a wellhead in West Texas, than for assets that are more easily collectible, such as a fleet of vehicles in New York City. Because there are many lease specific factors, such as specialization and collectability, that impact a lender's required yield, lessees should consider an adjustment to the incremental borrowing rate produced by LeaseSCRE to reflect lease specific factors.

Conclusion

ASC 842 requires that companies record their operating leases on their balance sheets, with corresponding assets and liabilities. To effectively do this, companies need to be aware of their incremental borrowing rate. For companies that do not have access to the necessary inputs required to calculate the incremental borrowing rate, A&M's lease accounting tool, LeaseSCRE, can help, using a three step approach: inputting financial data into A&M's machine learning tool, SCRE, for a credit rating estimate, deriving the unsecured borrowing rate using the appropriate CDS curve, and adjusting the rate to reflect collateralization.

Sign up for LeaseSCRE

Exhibits

Exhibit 1: CDS spreads are traded on a large, active market

"The market for credit default swaps (CDSs) has grown from an exotic niche market to a large and active venue for credit risk transfer—making it one of the most significant financial innovations of the last decades."

Source: "General Description of the Credit Rating Process as of May 16, 2018." *S&P Global Ratings*, 16 May 2018, www.standardandpoors.com/ru_RU/delegate/getPDF;jsessionid=6316ABAD8F1883716A42DFE318375A5A?articleId=2053416&type=COMMENTS&subType=REGULATORY.

Exhibit 2: Overview of Machine Learning Techniques and Processes

Machine Learning is a subset of Artificial Intelligence that is focused on algorithms and statistical models that computer systems use to progressively improve their performance on a specific task. Machine Learning tasks typically involve discovering the relationship between a set of data (features) and a set of results (labels) that the practitioner knows to be valid.

When applying Machine Learning to solve problems, practitioners will start with a set of features (in this instance, a company's financial results and financial statements) that are expected to explain a result (in this case, a company's credit rating).

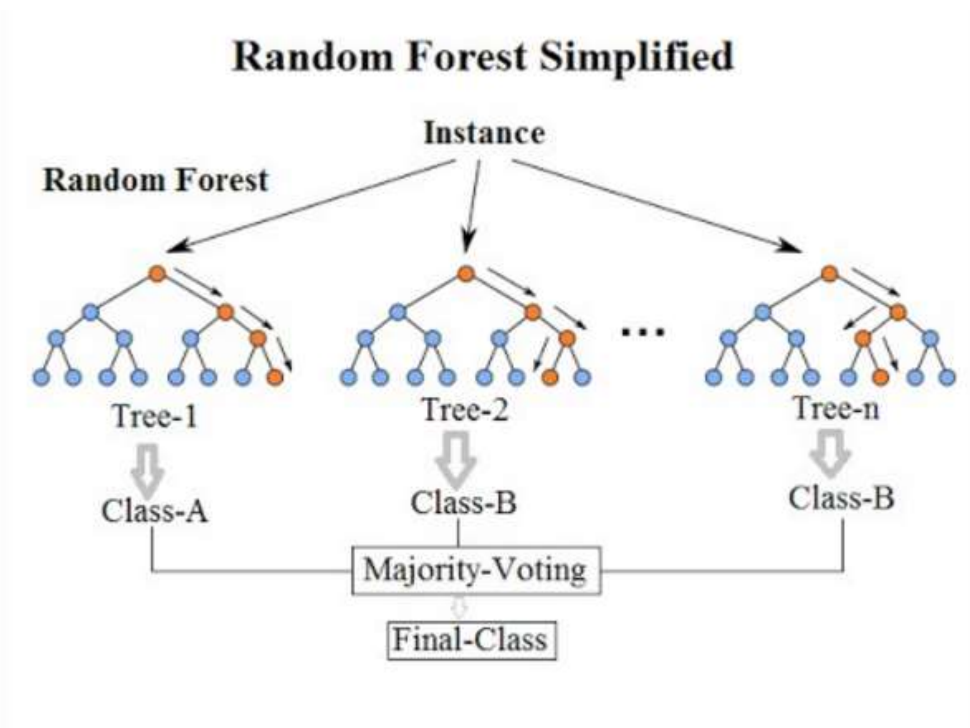
Generally, when data is loaded into a machine learning algorithm the data will be split into a training dataset and a testing dataset. The algorithm will then "train" itself to use the training set's features to prediction the result for each observation.

The methodology applied to making predictions is specific to each individual algorithm. For instance, decision tree algorithms will use the features to construct a decision tree that makes predictions, while k-nearest neighbors algorithms look for observations with similar features to make a prediction.

Once the algorithm is trained, it then uses the testing dataset to measure its accuracy when making predictions. Assuming proper data controls are used in the process of splitting between training and testing data sets, this will give a view of how accurate the algorithm is when predicting observations that were not included in the training data set. Our reported accuracy of SCRE is based on the accuracy of predicting the results of observations in the testing dataset.

SCRE output	SCRE converted
1.3125	AA+
2.0625	AA
3.875	A+
4.0625	A+
5.9375	A-
5.9375	A-
7	BBB+
8.25	BBB
9	BBB-
9.3125	BBB-
11.4375	BB
11.6875	BB-
13	B+
13.8125	B
15	B-
13.5625	B
16.4375	CCC+
17.125	CCC

Exhibit 3: Overview of random forest algorithm



Here is how such a system is trained; for some number of trees T:

1. Sample N cases at random with replacement to create a subset of the data (see top layer of figure above). The subset should be about 66% of the total set.
2. At each node:
    1. For some number m (see below), m predictor variables are selected at random from all the predictor variables.
    2. The predictor variable that provides the best split, according to some objective function, is used to do a binary split on that node.
    3. At the next node, choose another m variables at random from all predictor variables and do the same.

Depending upon the value of m, there are three slightly different systems:

- Random splitter selection: m =1
- Breiman's bagger: m = total number of predictor variables
- Random forest: m << number of predictor variables. Brieman suggests three possible values for m: ½√m, √m, and 2√m

Running a Random Forest. When a new input is entered into the system, it is run down all of the trees. The result may either be an average or weighted average of all of the terminal nodes that are reached, or, in the case of categorical variables, a voting majority.

Source: *A Gentle Introduction to Random Forests, Ensembles, and Performance Metrics in a Commercial System*, CitizenNet Blog, 9 Nov. 2012, blog.citizennet.com/blog/2012/11/10/random-forests-ensembles-and-performance-metrics.

Exhibit 4: Sample size for CDS spreads is statistically significant

Minimum Sample Size for Statistical Significance	
Margin of error (percent)	0.35
Confidence interval	95%
Z-score	1.959963985
Standard deviation	2.111511483
Minimum Sample Size	139.8128178

Exhibit 5: S&P considers industry information in its credit rating assessment

As part of their credit ratings process includes an assessment of industry and sector risk as well as company risk. In performing their analysis S&P focuses on a) sector / industry cyclicality and b) competitive risk and growth within the sector / industry. Cyclicality assessments are calibrated across industries using hypothetical stress scenarios while competitive risk analyses include analyses of:

- Effectiveness of industry barriers to entry;
- Level and trend of industry profit margins;
- Risk of secular change and substitution of products, services, and technologies; and
- Risk in growth trends

S&P's methodology assesses the risks within different subsectors of an industry within the analysis of a firm's competitive position.

Source: "General Criteria: Methodology: Industry Risk" *S&P Global Ratings*, 19 November 2013, https://www.spratings.com/scenario-builder-portlet/pdfs/IndustryRisk.pdf

Exhibit 6: There is a weak relationship between the unsecured-secured loan spread and credit rating

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.43034859
R Square	0.185199909
Adjusted R Squa	0.179541575
Standard Error	1.885808447
Observations	146

ANOVA

	df	*SS*	*MS*	*F*	*gnificance F*
Regression	1	116.3985	116.3985	32.73047	5.91E-08
Residual	144	512.1034	3.556274		
Total	145	628.5019			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	-1.927591211	0.552563	-3.48846	0.000645	-3.01977	-0.83541	-3.01977	-0.83541
Rating	0.287312567	0.05022	5.721055	5.91E-08	0.188049	0.386577	0.188049	0.386577