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Estimating a Credit Rating for Accounting Purposes: A Quantitative Approach

DAVID DELGADO-VAQUERO [a], JOSÉ MORALES-DÍAZ [b]

[a] *EY Corporate Treasury, Calle Raimundo Fernández Villaverde 65, 28003 Madrid, España. E-mail:* david.delgadovaquero@es.ey.com

[b] *Instituto de Estudios Bursátiles (IEB), Calle Alfonso XI, 6, 28014 Madrid, España. E-mail:* jose.morales@claustro-ieb.es

ABSTRACT

Under IFRS accounting standards, there are many situations in which the credit quality of a counterparty must be estimated. These include, for example, credit value adjustment of derivatives under IFRS 13; expected loss provisioning under IFRS 9; or own borrowing rate estimation under IFRS 16. In many cases, the inputs needed (generally a conditional probability of default (PD) or a yield to maturity (YTM) can be directly observed in the market or inferred from the quoted price of financial/credit instruments (e.g. liquid par CDSs or bonds), but in other cases this information is not available. With regard to the latter, we propose two models for internally estimating the credit quality of a counterparty as a basis (a first step) for obtaining the corresponding PD or YTM for said counterparty. The models (Financial Ratios Scoring and Merton KMV Structural Model) are based in part on previous literature, but they are more "universal" and better adapted to accounting purposes. For inputs, the models use public information about the counterparty (primarily financial information obtained from financial statements and other market inputs), and comparable companies.

Keywords: IFRS, Credit Rating, Credit Scoring, Probability of Default, Fair Value.

Estimación del Rating Crediticio para Contabilidad: Un enfoque cuantitativo

RESUMEN

Bajo las NIIF hay muchas ocasiones en las que se necesita estimar la calidad crediticia de una contraparte. Por ejemplo: a la hora de calcular el ajuste por riesgo de crédito de los derivados en NIIF 13, para calcular la provisión por la pérdida esperada bajo NIIF 9 o para estimar el tipo de interés incremental de la propia deuda bajo la NIIF 16. En muchos casos, los inputs necesarios (generalmente la probabilidad de *default* condicionada -PD- o una tasa interna de rentabilidad –YTM- pueden observarse directamente en el mercado o inferirse del precio cotizado de instrumentos financieros/de crédito (como CDSs o bonos), pero en otros casos esta información no está disponible. Para estos casos proponemos dos modelos de estimación interna de la calidad crediticia de una contraparte como base (como primer paso) para obtener la correspondiente PD o YTM. Los modelos (*Financial Ratios Scoring model* y *Merton KMV Structural Model*) se basan, en parte, en literatura previa pero son más "universales" y adaptados a los requerimientos contables. Los modelos utilizan, como inputs, información pública de la contraparte (básicamente información de los estados financieros y otros inputs de mercado) y de empresas comparables.

Palabras clave: NIIF, rating crediticio, *scoring* crediticio, probabilidad de quiebra, valor razonable.

JEL Classification: M41, G12, G32, C63

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1. INTRODUCTION

Over the last ten years, IFRS[1] accounting standards have changed significantly in areas such as *fair value*, *financial instruments*, *lease accounting*, and *revenue recognition*. Generally, the new standards issued entail a higher use of judgment and estimations, which renders the role of preparers and auditors far more difficult. According to Heidhues and Patel (2011), the exercise of accountants' professional judgment has increasingly been recognized as an important and controversial topic.

In this sense, for one purpose or another, several recently issued standards require entities to estimate the credit quality of a third party or their own credit quality. For example, following the implementation of IFRS 13 ("Fair Value Measurement"), when measuring derivatives' fair value, entities must consider the credit risk adjustment, which generally entails estimating the PD of the derivative's counterparty and the own PD, among other inputs (see IFRS 13 paragraphs 3, 42 - 44 and 69) . In another example, under IFRS 16 ("Leases"), when a lessee discounts future lease cash-flows, if the implicit lease rate is not available, the entity must estimate its own borrowing rate for buying a specific asset with a specific maturity (see IFRS 16 paragraphs 26, 41 and 45).

In some cases, the inputs required (as per the previous examples, the PD or the loan interest rate/YTM[2]) can be directly inferred from observable market information such as CDS[3] spread quotes or a bond price quote[4]. In other cases, however, this information is not available. The counterparty whose credit quality needs to be estimated may not have quoted CDSs or bonds, nor a credit rating[5] issued by an independent rating agency. In such cases[6], entities can implement a different methodology for internally estimating the credit quality

[1] International Financial Reporting Standards (IFRS) issued by the International Accounting Standards Board (IASB). In Europe, IFRS are applied by quoted entities for the preparation of their consolidated financial statements (see Regulation (EC) No 1606/2002 of the European Parliament and of the Council). In many countries, local accounting standards are inspired by IFRS or are a transposition of IFRS. See http://www.ifrs.org/use-around-the-world/use-of-ifrs-standards-by-jurisdiction/ for a detailed study on the use of IFRS standards by jurisdiction.

[2] Yield-to-maturity.

[3] Credit Default Swap.

[4] Or even from internal information such as the yield-to-maturity of a recently obtained, representative banking debt.

[5] Credit ratings are a summary of a firm's expected future creditworthiness. They represent an evaluation of the credit risk of company, i.e. they are related to the probability that a company will default. The higher the rating, the lower the credit risk, and the lower the probability of default. There are independent credit rating agencies that issue public credit ratings for companies/governments or specific bonds issuances. The four most important rating issuers are S&P (Standard & Poors), Moody's, Fitch and DBRS (Dominion Bond Rating Service).

[6] See IFRS 13 fair value hierarchy in Section 3.

(credit rating) of a company as a basis for obtaining a PD or a YTM/discount rate curve.

Within the field of finance literature, the interest in credit risk and credit rating has particularly increased since the 2008 subprime financial crisis. There is a line of research in which authors propose models for obtaining an internal credit rating in order to challenge the official credit rating issued by rating agencies, or to use it in the event that there is no official credit rating available. The first historical work was that by Altman (1968), which used five financial ratios in order to predict bankruptcy. Since then, many authors have also proposed models in which financial variables are used for estimating credit risk. See, for example, Merton (1974); Kaplan and Urwitz (1979); Ohlson (1980); Ederington (1985); Longstaff and Schwartz (1995); Duffee (1999); and Kamstra *et al.* (2001).

More recently, Creal *et al.* (2014) proposed a marked-based rating which makes direct use of the prices on traded assets. The authors use asset pricing data to impute a term structure of risk neutral survival functions or default probabilities. Firms are then clustered into ratings categories based on their survival functions using a functional clustering algorithm. They compare their ratings to S&P and find that, over the period 2005 to 2011, their ratings lead S&P's for firms that ultimately default.

Tsay and Zhu (2017) proposed a two-step algorithm involving ARIMA-GARCH modelling and clustering in order to obtain a market-based credit rating utilizing easily obtained public information. The algorithm is applied to 3-year CDS spreads of 247 publicly listed firms. The authors compare the ratings obtained with the ratings given by agencies, and show that such market-based credit rating performs reasonably well. Jansen and Fabozzi (2017), assuming a given recovery rate, use the CDS-implied default probabilities to cluster them in rating groups.

However, there are few proposed models for obtaining an internally developed credit rating that fulfil all the following criteria at the same time:

A) Specifically addressed to accounting purposes (i.e. for complying with accounting requirements) (see section 2.2).

B) Adaptable, enabling almost any entity to use it.

C) Comparable, so that the results can be compared to market information.

D) Able to be applied to one specific counterparty/company (without requiring the development of a complete series of statistical data obtained from too great a range of companies simultaneously).

E) Applicable in any jurisdiction.

F) Able to be implemented by obtaining public information which is readily available, such as the entity's sector; the credit rating issued by official rating agencies for other companies in the same sector/country; the entity's financial statements, etc.

G) The output provided is a credit rating under a scale comparable to the ratings used by rating agencies: S&P, Moody's and Fitch. This will make it easier to find companies with similar credit risk and which do also have a public credit rating.

The aim of this paper is to propose two models which entities can follow in order to estimate the internal credit rating of a company, while also complying with the requirements outlined above. In one of the models, an internal credit rating is obtained, and said credit rating may be used (in combination with other information) as a basis for estimating a PD or YTM. In the second model, a PD is directly obtained, and through said PD an internal credit rating may be assigned. As we will see (Section 3), IFRS fair value hierarchy should be followed and, therefore, if observable market information is available, that information should be prioritized.

The remainder of the paper is organized as follows: in Section 2 we will introduce the general accounting context and develop several cases in which a credit rating for a company may be required under IFRS. In Section 3, we will analyze IFRS 13 fair value hierarchy. Section 4 includes the introduction and basis for the two models, while in Section 5 explains the models in further detail. Section 6 includes the final conclusions.

2. ESTIMATING CREDIT QUALITY UNDER IFRS

2.1. General context

Since 2007, the world economy has gone through a critical period. A crisis in terms of both debt and financial confidence arose rapidly and spread through many countries, particularly affecting the United States and Europe. Financial markets suffered significant credit uncertainty, which in turn affected almost every counterparty involved in a transaction.

An increasing tension of weak debts, both on the micro and macro scale, emphasized the threat existing to the financial stability of not only specific entities, but also the market as a whole and even countries. The credit reliability of counterparties and clients became the main point of interest for a growing number of market participants, while leaving the market (price) risk and trading itself out of the main scope. Those investing in credit instruments started to consider them to be of even greater risk than other types of investments.

Against this background, the regulatory framework in many relevant jurisdictions focused on supervising credit and counterparty risk of financial markets and their participants, ensuring that the actual credit risk was reflected in both a bank's trading and banking book, as well as in the financial statements of any company involved in relevant financial transactions (particularly derivatives). From primary markets to OTC[7] derivatives (and with significant effects on retail clients), the change in principal credit risk factors has stimulated the research into more effective methods of credit and counterparty risk management.

2.2. New IFRS standards

As previously explained in Section 1, under IFRS accounting standards there are many scenarios in which a credit quality estimation is called for in order to obtain a PD or a YTM. In this sense, entities from many different sectors and sizes are currently facing a variety of situations which require them to estimate the credit quality of a third party (or their own credit quality), and that information may not be observable in the market. Some such situations are explained below.

1) The Credit Risk Adjustment of Derivatives

The IFRS 13 standard was issued in 2011, and came into effect for annual reporting periods commencing on or after 1st January 2013. This standard represents a general fair value framework. If another IFRS requires or permits the use of fair value as a measurement basis, generally the entity should follows IFRS 13 for measuring the fair value (with the exceptions included in paragraphs 6 and 7 of IFRS 13).

Prior to IFRS 13, and as a general rule, in order to measure the fair value of a financial derivative, future cash flows were estimated using different techniques, and these cash-flows were subsequently discounted using the "risk free" curve (based on interbank rates, such as the Swap-Euribor curve for 6 months).

In this regard, it was assumed that the possible credit risk adjustment that could arise was not material, or that the credit risk assigned to both counterparties was netted. An adjustment for credit risk was only carried out in those scenarios where incurred losses had to be provisioned. In these cases, the positive value of the derivative was priced downwards in order to reflect an estimated recoverable amount.

IFRS 13 clarified that when measuring the fair value of derivatives, credit risk must always be considered (see paragraphs 3, 42 - 44 and 69 of IFRS 13). This includes both the risk that the derivative may end with a positive value and the counterparty does not meet its obligations (CVA - Credit Value Adjustment, which in some cases was already calculated)[8], as well as the risk that the

[7] Over-the-counter.

[8] CVA is not specifically mentioned in IFRS 13. Nevertheless, the standard states that an entity should measure the fair value of an asset or a liability using the assumptions that market participants would use when pricing the asset or liability, assuming that market participants act in

derivative may end with a negative value and the company itself does not meet its obligations (DVA - Debit Value Adjustment, which was not calculated prior to IFRS 13).

CVA and DVA adjustments are generally estimated as follows (see Morales (2015) or Kenyon and Stamm (2012) among others for further details on CVA/DVA estimation):

$$CVA/DVA = (1-R)\int_0^T E_t^{\mathbb{Q}}\left[\left(P(0,t)\cdot V(t)^+\right]\cdot PD_c(t)\,dt \qquad (1)$$

where $E_t^{\mathbb{Q}}[(P(0,t)\cdot V(t)^+]$ is the expected discounted value of the derivative's positive exposure $V(t)^+$ under a probability measure $\mathbb{Q}$; $PD_c(t)$ is the conditional probability of default at *t*; and R is the estimated recovery rate.

Therefore one of the necessary inputs for CVA estimation is the conditional PD of the counterparty between $t = 0$ and $t = T$ while in the case of DVA estimation, one of the necessary inputs is the own conditional PD in the same context. This may be obtained from quoted CDS or bonds, but in many cases this information is not available.

2) Financial Assets Expected Loss Provision

IFRS 9 is the financial instruments accounting standard that will replace IAS 39 for annual reporting periods commencing on or after 1st January 2018. One of the areas in which IFRS 9 will have a higher impact is the new impairment model (applicable to financial assets not measured at fair value through profit and loss, lease receivables, contract assets and financial guarantee contract - see IFRS 9.5.5.1).

IAS 39 followed an incurred loss model: an impairment loss could not be recognized until it was incurred. Additionally, in terms of the "generic" provision, only what was known as Incurred But Not Reported (IBNR) losses could be recognized: losses related to debtors for which, at the date of the financial statements, the credit event has occurred but has not yet been revealed/reported.

Conversely under IFRS 9, as soon as the debt instrument is recognized, at least part of the expected losses should be recognized. Loans are classified in three steps: step 1, step 2 and step 3. In step 1, 12-month expected credit losses are recognized, while lifetime expected credit losses are recognized in steps 2 and 3.

Generally, the expected credit losses are calculated as $EAD_t \cdot PD_t \cdot (1-R)\cdot P(0,t)$.[9] (a similar formulation to that of CVA/DVA calculation). Therefore, one

their economic best interest. CVA is considered by market participants when pricing the derivative.

[9] EAD_t is the Exposure at Default at time *t*; PD_t is the cumulative Probability of Default at *t*.

of the necessary inputs for calculating the expected credit losses is the PD of the borrower. In step 1, PD refers to the next 12 months, while in steps 2 and 3 it refers to the instrument maturity. This may be obtained from quoted CDS or bonds, but in many cases this information is not available.

3) Lease accounting (lessees)

IFRS 16 is the new lease accounting standard that will replace the current IAS 17 for annual reporting periods commencing on or after 1st January 2019.

The implementation of IFRS 16 will specifically affect contracts in which the entity is the lessee. In the majority of these contracts, the entity will have to apply the so-called “capitalization model” which the new standard introduces.

In the capitalization model, the lease asset (right-of-use) and the lease liability are initially measured by discounting future lease payments. Subsequently, the asset is depreciated (in most cases on a straight-line basis), and the liability is accounted for as a debt in which the financial expense is accrued based on the discount rate used.

In addition, in case of subsequent modification of the lease payments (due to changes in variable payments, changes in the lease term, etc.), the lease liability should be recalculated; that is, future cash-flows should be discounted once again (using the original interest rate in some cases and a new interest rate in others).

IFRS 16 establishes the following in relation to the interest rate to be used by a lessee when discounting future lease payments (IFRS 16.26, 41 and 45):

1) In principle, the so-called “implicit interest rate in the lease” should be used. This is the rate that the lessor obtains from the financing transaction implied by the lease.
2) The IASB recognizes that in many cases, the lessee will not be able to obtain the interest rate implicit in the lease because he/she does not possess information on aspects such as the initial costs incurred by the lessor or the residual value of the asset at the end of the lease period (IFRS 16. BC161). In these cases, IFRS 16 allows for the use of the “lessee’s incremental borrowing rate”. This is the rate that the lessee would have to pay on a debt in order to buy the leased asset while taking into consideration the following aspects (IFRS 16.BC161):
   - Moment in time.
   - The maturity of the lease.
   - The economic environment in which the transaction occurs.
   - The credit quality of the lessee.
   - The nature and quality of the collateral.

Generally speaking, it is expected that many entities will use the incremental borrowing rate instead of the lease implicit rate (see Morales and Zamora, 2017 and Morales and Zamora, 2018). Therefore, an estimation of the lessee's credit quality is required in order to obtain the borrowing rate.

3. IFRS 13 FAIR VALUE HIEARCHY

The way in which a company should consider the corresponding credit quality in the situations described in Section 2, and the way in which the inputs are developed should be consistent with the fair value hierarchy included in IFRS 13.

Fair value hierarchy refers to the inputs used in order to measure fair value. IFRS 13 prioritises observable inputs over those that are not observable (i.e. that are internally developed by an entity). There are three levels within IFRS 13 fair value hierarchy (IFRS 13 Appendix A):

- Level 1 inputs: quoted prices (unadjusted) in active markets for identical assets or liabilities that the entity can access at the time of measurement.
- Level 2 inputs: inputs other than quoted prices included within Level 1 that are observable for the asset or liability, either directly or indirectly.
- Level 3 inputs: unobservable inputs for the asset or liability.

IFRS 13 focuses on prioritizing the inputs used in the valuation techniques and not the techniques themselves (see IFRS 13.74), (however, the availability of inputs could affect the valuation technique used).

Therefore, as stated above, when obtaining a PD or a YTM within this context, it is important to consider fair value hierarchy. For example, in order to obtain a PD for a specific counterparty and maturity:

1) The best input would be the PD calibrated with CDS spreads (on bonds issued by the same counterparty with the same maturity), quoted in an active market.
2) Should that information not be available, other possible sources in order to estimate the PD are:
    - The quoted YTM of bonds issued by the same counterparty with the same maturity in an active market.
    - The quoted CDSs spread (over bonds issued by the same counterparty with the same maturity) in a non-active market.
    - The quoted YTM of bonds issued by the same counterparty with the same maturity in a non-active market.
    - The quoted CDSs spread (over bonds issued by the same counterparty with similar maturity) in a non-active market. The spread should be

adjusted for the difference in maturity.

- The quoted YTM of bonds issued by the same counterparty with similar maturity in an active or non-active market. The PD is adjusted for the difference in maturity.

3) Should the specific counterparty not have quoted CDSs or bonds, nor a public credit rating, the PD could also be obtained from quoted CDSs or bonds of other companies with the same rating and characteristics (sector, country, size, etc.).

4) Should the specific counterparty not have quoted CDSs or bonds, nor a public credit rating, the entity could internally estimate a credit rating for the specific counterparty in order to obtain the PD from quoted CDSs or bonds of companies with the same rating and characteristics (sector, country, size, etc.). In both cases, as much market information as possible should be used.

The models proposed in the following Sections would only be used in the case of this last scenario.

On the other hand, in many cases, the fact that the credit risk should be considered in a fair value measurement makes this fair value be classified as Level 3. This occurs when the corresponding input related to the credit risk is not observable and is not considered as non-significant in relation to the measurement.

4. CREDIT MODELS PROPOSED: AN INTRODUCTION

Over the last decades, a significant number of quantitative models for estimating and pricing credit and counterparty risk have been developed, recalibrated and improved. Default risk models such as the ones proposed by Merton (1974), Longstaff and Schwartz (1995) and Duffee (1999), among others, have constituted a benchmark with regard to credit risk, and more recently counterparty risk for derivative markets.

In most cases, credit risk models concentrate on one single important issue: the default risk of an entity. The term “entity” may be understood as a counterparty; as an issuer (public or private); or as a bank’s retail client. However, the term “default” is subject to different interpretations (particularly as regards when and for how long an entity has defaulted, or whether a non-payment may be considered as a default event or not).

Default risk can be generally measured in three ways: by using quantitative or statistical tools (information from equity, credit markets and financial instruments); by using qualitative data (entity structure; business estimations; information regarding the entity’s governance and risk appetite; etc.); or by using a combination of both quantitative tools and qualitative data.

In the first model we propose, the company's financial statements information has the most significant role, whereas in the second model, market risk factors will constitute the main inputs. In other words, we propose using quantitative tools[10] without specifically considering qualitative data. This is essentially due to the following factors:

1) Over the last number of years, quantitative models have been taking new assumptions into account and covering recent scenarios in terms of default events and recovery rates (see, for instance, Moody's latest reports on default risk and recovery rates (Moody's, 2017)). This means that in general terms we can say that the more reliable the financial information and current market data the model uses as inputs, the more effective it will be in estimating a probability of default or assigning a credit rating.
2) Qualitative aspects - such as business perspectives; corporate governance; the regulatory and competitive environment; and financial policy, among others - are highly subjective factors, and it is difficult to measure them using quantitative metrics. Such aspects are mainly covered by rating agencies, which have specialized research areas for each sector and country, where qualitative aspects change from one company to another.

Both of the models proposed are the result of our practical research for the conducting of credit and counterparty risk analysis, which forms part of our work on a daily basis. One of the models is already known among professionals and practitioners (Merton's - KMV[11] Structural Model), nevertheless we provide with some guidance in order for the model to be applicable under an illiquid market information scenario. The proposed models are as follows:

1) Financial Ratios Scoring (FRS) model. This model has been internally developed by us and we have implemented it in a wide range of companies and sectors. The model tries to cover the main aspects behind the information implicit in a company's financial statements. Depending on the values of several key balance sheet and profit and loss account ratios, the company is allocated to a certain position (score) within a consistent distribution of previously rated[12] companies belonging to a specific sector. The model's theory relies on the fact that the better score of key ratios

[10] The first model proposed uses comparable companies' agency ratings to statistically estimate a credit rating. Therefore, qualitative aspects are also covered to a certain degree. However, those aspects are not directly modelled nor measured therein, as generally speaking medium-sized companies are not willing to employ many resources to cover them. With regard to the second model, the methodology focuses on the simulated probability that assets cannot cover liabilities at a point of time in the future, hence qualitative aspects are implied in the factors affecting the asset simulated path.

[11] KMV: Kealhofer, McQuown and Vasicek.

[12] Companies with an official credit rating issued by a credit agency.

within a sector, the better the general score, and subsequently the better the credit rating. This particular model is most intensive in terms of data collection, but it does prove to be highly consistent since the model's inputs are calibrated with the financial information of companies which do have an agency rating.

2) Merton's - KMV Structural Model. This model has been used and developed by risk professionals and practitioners for several years, and it is still among the most powerful tools available for estimating short term default probability. The model's basic premise is that a company may be seen as a call option: when the value of the company's assets decrease below the value of the company's debt, the company's value is zero or near zero. This situation is considered to be a credit event, and the probability of such an event is obtained through the model. By considering market probabilities of default and their link to credit ratings, we are able to estimate a short term credit rating for a given company.

Although the essence of each of the models is different, both their inputs and objectives are similar, even more so than initially expected (they do tend to converge). This fact provides the analyst with the possibility of using either one of the models individually, or of using both of them in order to conduct the analysis.

The FRS model is clearly affected by the performance of financial ratios, but in general terms the ones with higher relevance in terms of credit risk are those related to debt and interest coverage, leverage or liquidity. Growth and profitability are also considered, but linked to liabilities and equity. The Merton's - KMV model focuses on the assets' performance in relation to the coverage of liabilities. Hence, leverage and coverage indicators are inherent in both models, and they react the in same manner and also demonstrate similar behaviour with regard to said credit risk indicators.

As the FRS model relies on accounting information, one possible model limitation is related to earning manipulation. Alissa *et al.* (2013) identify firms that deviate from expected credit ratings and demonstrate that these empirically estimated credit rating deviations are associated with earnings management activities. Their results suggest that firms below or above their expected credit ratings may be able to successfully achieve a desired upgrade or downgrade through the use of earnings management.

5. PROPOSED CREDIT RISK MODELS. METHODOLOGY, RISK FACTOR CALIBRATION AND IMPLEMENTATION

5.1. Financial Ratios Scoring model

This model focuses on reflecting the position (score) of a company within a representative group of rated companies, so as to provide the company with a credit rating in line with its associated score.

With regard to the score:

- it is also termed “percentile” in the model. It is configured on a basis where 1 represents the worst and 100 the best position.
- it will depend on the values of the financial ratios selected, and therefore on the position of each financial ratio within its group (hereinafter “distribution”).

The construction of the model follows four steps, namely:

Step 1. A set of key financial ratios are defined for the company’s sector (usually financial ratios belonging to categories and/or credit metrics such as coverage, leverage, liquidity, profitability and growth). We propose the use of the ratios included in Table 1 below as a general framework. These ratios are extensively used, at least in part, by rating agencies, and they represent the key financial dimensions that act as drivers for a rating profile (see, for example, Moody’s 2017 (2)). Moreover, these ratios are also chosen given that the majority of them are usually available for calculation using the company public financial statements.

It is worth noting the fact that each sector has its own characteristics, so additional ratios could be defined to represent a credit metric for a specific sector (e.g. Generation Cost -Utilities-, Loan to Deposits -Banking- or Passenger Load -Airlines-). However, as this paper is intended to introduce the methodology for any given company regardless the sector, the below table covers a general profile for most of companies, whereas specific ratios are out of our scope. It should be noted that, as it will be explained in next sections, the intrinsic characteristics of a sector are disclosed when calibrating the ratio weights so that the variable “sector” is somehow covered by this methodology.

Table 1
Ratios Used in the FRS Model

Ratios used in the Analysis	Credit metric
Interest Expense/Sales	Coverage
EBITDA/Interest Expense	Coverage
(Liabilities - Cash & Securities)/Assets	Leverage
Retained Earnings/Liabilities	Leverage
Current Assets/Current Liabilities	Liquidity
Cash & Securities/Current Assets	Liquidity
Return on Assets (ROA)	Profitability
Return on Equity (ROE)	Profitability
Sales growth YoY, last 5y	Growth

Source: Compiled by the authors.

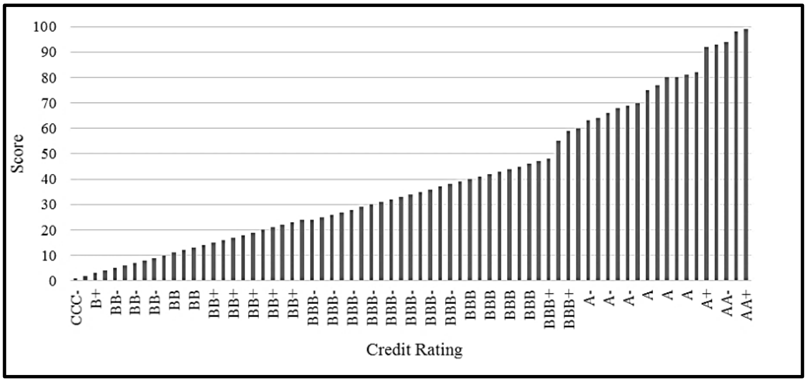
- "Interest expense/Sales" and "EBITDA/Interest Expense" (coverage ratios) analyse to what extent the entity generates sufficient resources in order to be able to pay the interests related to external debt:
    - In the first ratio, the higher the level, the lower the coverage (less sales income is available to pay the interest expense).
    - In the second ratio, the higher the ratio level the higher generated surplus (and the higher the coverage).

  Both coverage ratios become critical since a default event is usually understood as the situation when a company is not able to entirely pay the short term debt, so that these two ratios can act as credit health signals.
- "(Liabilities - Cash & Securities)/Assets" analyses the leverage level i.e. to what level de entity is indebted. The higher the ratio level the higher the debt level of the entity (and higher the credit risk) because there are less assets that guarantee the payment of the debt.
- "Retained Earnings/Liabilities" also analyses the leverage level. It compares the result with the entity's debt. In this sense, the higher the ratio the lower the relative leverage level.
- "Current Assets/Current Liabilities" and "Cash & Securities/Current Assets" analyse the liquidity of the entity. The first ratio represent the excess of current assets over current liability (the higher the ratio level, the higher the liquidity level). The second ratio analyses to what extent current assets are composed by liquidity (the higher the ratio level, the higher the liquidity level).
- ROA and ROE analyse the profitability of the company. They calculate the return in relation to the assets (ROA) and the return in relation to the equity (ROE).
- "Sales growth" analyse the growth in the sales figure. The company growth can be analyzed via several ways (in terms of assets, sales, EBITDA or Net Profit, among others). We have chosen sales growth given the fact that the other metrics might be biased due to the company activity. Sales figures usually are isolated enough to be considered as a good estimating of the company performance (always taking into consideration their relevancy in comparison to the above credit metrics).

Step 2. A database is constructed which includes a set of rated companies linked to their rating score. The companies chosen should belong to the same sector and country (if possible) as the company being analyzed, and should have recently been rated by a relevant credit rating agency (i.e. S&P, Moody's, Fitch or DBRS). A general score is assigned to each comparable company, hence each one will be ranked according to its position (percentile, between 1 and 100) within the entire vector of companies. This position represents the score.

During 2017, we input the information required into a database in order to build the following cumulative distribution function with regard to a specific sector and ratio:

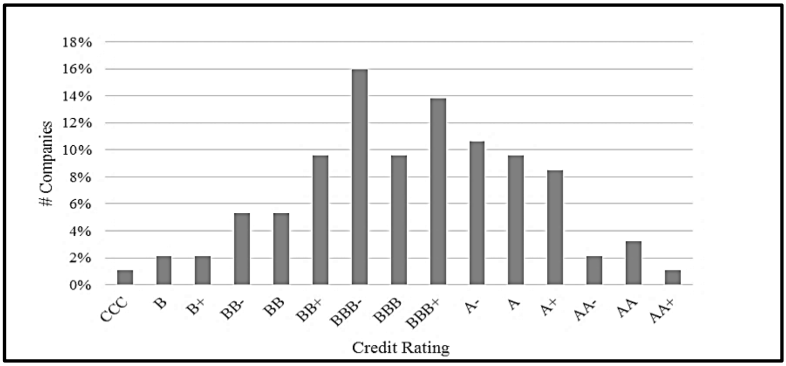
Figure 1
Distribution of Scores per Credit Rating



Source: Compiled by the authors.

As may be seen, the credit rating is directly related to the score ("position" or "percentile") within the distribution. Certain companies with an equal rating are scored slightly differently according to their outlook, size and debt coverage. In the example above, this means that we find 13 companies with the same rating (BBB-) between percentile 25 and 37. This is normal given the fact that there are more companies rated between BBB- and BBB+ than in any other rating bucket. Figure 1 above represents a cumulative distribution of 63 rated companies. Its corresponding probability density function is shown below:

Figure 2
Density function of Credit Rating



Source: Compiled by the authors.

Step 3. A database is built containing the ratios shown in Table 1 belonging to the companies used to shape the distribution and density functions. The methodology is based on setting each ratio of the comparable companies within its respective distribution, so that each ratio has a score with respect to its own distribution. The ratio distribution (vector) should be as granular as possible.

Step 4. A matrix is prepared which retrieves the relationship between the comparable companies' rating, their general score, and the score of each ratio. Table 2 contains an example:

Table 2
Scoring table by Component Scores

			Component Scores				
Company Name	**L/T Company Rating**	**Credit score**	**Profitability**	**Leverage**	**Coverage**	**Liquidity**	**Growth**
Company 1	Company 1 L/T Rating	Company 1 Credit Score	Company 1 Profitability Score	Company 1 Leverage Score	Company 1 Coverage Score	Company 1 Liquidity Score	Company 1 Growth Score
Company 2	Company 2 L/T Rating	Company 2 Credit Score	Company 2 Profitability Score	Company 2 Leverage Score	Company 2 Coverage Score	Company 2 Liquidity Score	Company 2 Growth Score
Company 3	Company 3 L/T Rating	Company 3 Credit Score	Company 3 Profitability Score	Company 3 Leverage Score	Company 3 Coverage Score	Company 3 Liquidity Score	Company 3 Growth Score
Company 4	Company 4 L/T Rating	Company 4 Credit Score	Company 4 Profitability Score	Company 4 Leverage Score	Company 4 Coverage Score	Company 4 Liquidity Score	Company 4 Growth Score
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Company n	Company n L/T Rating	Company n Credit Score	Company n Profitability Score	Company n Leverage Score	Company n Coverage Score	Company n Liquidity Score	Company n Growth Score

Source: Compiled by the authors.

In summary, the database should be fed with the following inputs:

1) The names of the comparable companies, their long term credit rating and general score.
2) The ratios of the comparable companies and their respective scores.
3) The ratios of the analyzed company and their respective scores.

Once the database with the sectorial ratios has been built, we now are able to assign a score to each ratio of the company analyzed. The question now is that of how we can use the ratios' score in order to assign a rating to the company.

Firstly, we need to know the representativeness of each ratio within the rating assigned to each company. We know that the ratios used do not entirely cover the wide range of risk factors considered by rating agencies (although they do implicitly include qualitative factors). Given the nature of our analysis, it is clear that the overall credit score is a dependent variable and that the ratios' scores are the independent variables, assuming there are risks not covered in the model. Our previous practical research concluded that the use of an ordinary Least Squares methodology in order to calibrate a linear regression represented by a weighted sum of the ratios scores retrieves highly accurate results in terms of the model's goodness-of-fit. This is to say that we are able to estimate the overall credit score of a company as follows:

$$Score_{company_i} = \sum_{j=1}^{n} Score_{Company\ ratio_j}\ \beta_j \qquad (2)$$

and subsequently we may calibrate each β_j by using the database of companies as outlined in previous paragraphs.

For the sake of clarity and to allow for a replica exercise for the reader, we present the following example data in order to calibrate each β_j for a given sector:

Table 3
General and Ratio scores for a sample of comparable companies

			Component Scores				
Company Name	**L/T Company Rating**	**Credit score**	**Profitability**	**Leverage**	**Coverage**	**Liquidity**	**Growth**
Company 1	**BB+**	15	2	29	14	53	38
Company 2	**BBB+**	61	10	64	55	31	72
Company 3	**BBB-**	37	12	24	54	48	33
Company 4	**BBB+**	53	86	12	62	25	95
Company 5	**BBB-**	24	61	13	52	5	84
Company 6	**BBB+**	60	84	37	59	28	62
Company 7	**BBB-**	25	5	6	44	19	94
Company 8	**BBB**	45	8	97	14	79	14
Company 9	**BB+**	22	46	16	39	16	59
Company 10	**BBB+**	58	80	42	70	49	58
Company 11	**B**	2	19	1	22	1	29
Company 12	**BBB-**	24	65	13	48	26	45
Company 13	**BBB-**	25	38	19	18	29	4
Company 14	**BBB+**	60	29	48	63	51	14
Company 15	**BBB-**	30	6	45	40	28	21
Company 16	**A**	91	51	83	95	62	90

Source: Compiled by the authors.

Following a Least Squares methodology, the following β_j[13] are obtained with regard to (2):

Table 4
β_j calibration for (1) with data set of Table 3

Profitability	**Leverage**	**Coverage**	**Liquidity**	**Growth**
5,45%	**42,27%**	**48,03%**	**3,25%**	**1,00%**

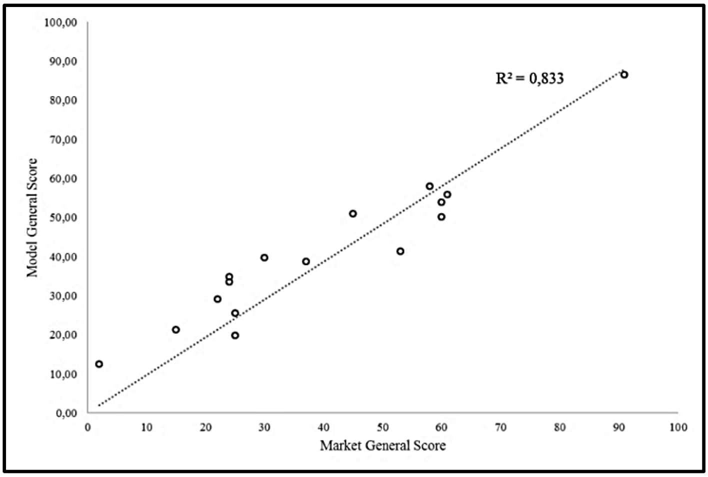
Source: Compiled by the authors.

The linear regression and the R^2 for the previous calibration are shown

[13] For model calibration, β_j are bounded between 0.01 and 0.9 with a total sum of 1.

below. The representativeness and goodness-of-fit of the model are sufficiently satisfactory to consider the model as consistent, as no high multicollinearity is found. It should be noted that not all sectors fit equally in a linear model, and the dependency on the database size and on certain ratios is relatively moderate. The analyst should select the sectorial ratios which represent the best the credit performance.

Figure 3
Linear regression plot for FSR model example



Source: Compiled by the authors.

The representativeness and goodness-of-fit of the model appears to be consistent with market general ratings.

Once the β_j are calibrated, there are two options for assigning the credit rating to the company. The first is straightforward: applying the model as (2) in order to obtain the company score. If, for example, we consider that the company analyzed has the following ratio scores:

Table 5
Ratio Scores of the company analyzed

Profitability	Leverage	Coverage	Liquidity	Growth
24	19	39	32	56

Source: Compiled by the authors.

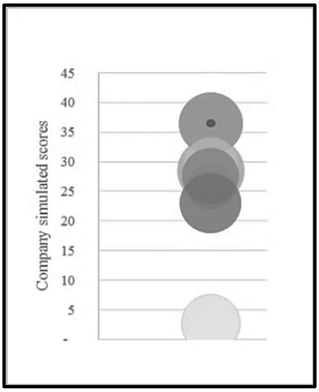
Then the model retrieves a score of 29.19, which means a BBB- rating in line with the score distribution shown in Figure 1.

We may also apply a solution to the model based on a difference-simulation methodology, which in turn covers as far as is possible the root mean square error, which in this example was 6.25. This is to say, while taking into account the existing convexity in the relationship between a company's general score and its implied credit rating, we propose that the weighted sum of differences between the analyzed company's ratio scores and those of each comparable company should be computed. Firstly we obtain the distance between the company analyzed and the comparable company. Thus the simulated company score will be equal to the sum of the weighted sum of differences and the current comparable company score.

$$Score_{company|comparable_i} = \left[\sum_{j=1}^{n} (Score_{Company\ ratio_j} - Score_{Comparable_i\ ratio_j}) \beta_j \right] + Score_{comparable_i} \qquad (3)$$

This is carried out in order to capture the actual difference between our computed rating and the theoretical rating that the analyzed company would have if a starting point were taken. Namely, we compute the weighted difference based on the calibrated β_j, but by applying the difference to the actual score of the comparable company, we place the analyzed company in a score according to a central point. This way, the regression error is covered to a certain degree. Each result may be considered as a simulation. The average of simulations will represent the company's score. The simulation plot may be seen below, and retrieves a concentration above a score of 32 (BBB-), with an average of 31.76 and a median of 32.84. This method also provides us with an idea as to the range in which the score can be placed. It would obviously be necessary to include many more companies in the database in order to perform a consistent simulation, but for the sake of clarity, this example has been carried out from the sample listed in Table 3.

Figure 4
Company score simulations performance



Source: Compiled by the authors.

5.3. Merton's - KMV Structural Model

This model was initially proposed by Merton (1974) and then adjusted for practical implementation by KMV (Vasicek, 1984). It may be viewed as a set of equations constructed in order to obtain the credit risk embedded in a company's equity price.

The idea underlying this second model is that equity prices are a sound predictor of a company's net assets value performance, and the fact that this in turn can be linked to the concept of liquidity and leverage management. It estimates default risk by using the relationship between equity, assets and liabilities.

5.2.1. Concepts and preliminary basis

The model assumes that a company will default when the value of its assets is not sufficient to pay the debts that the company should settle in the short- or medium-term. In this sense, when the value of the assets decreases below the value of the debts, the company's value is zero or near zero. The probability that this event will occur is the default probability of the company that we will link to a credit rating. At this stage, two aspects should be considered:

1) The need to estimate the probability that the value of assets will decrease below the value of the liabilities in a given period.
2) The need to carry out research in the credit market in order to link default probabilities and credit ratings.

With regard to the second aspect, credit rating agencies and financial vendors frequently perform studies that may be used (for example, Moody's or Reuters[14]). However, the first issue remains to be resolved.

The model proposed herein is based on a widespread methodology that estimates the probabilities of default based on the company's equity and its financial statements. The equity market will act as the predictor of the performance and volatility of the company assets. These two items are critical in order to estimate the probability of the assets' having a value lower than the debt value. As previously explained, the debt value constitutes the other significant factor: the higher the debt book value, the higher the probability of assets decreasing below said debt book value, within a certain timeframe.

5.2.2. Model theory (I): lognormal property of equity prices and Montecarlo simulation

As previously stated, the main concern of the model is to obtain the probability of assets value decreasing below debt value in the near future. In this

[14] This type of information is available to be purchased.

sense, we need to identify the "forward-looking" performance of the assets (i.e. the values they may take in the future).

For this purpose, we can perform a Montecarlo simulation in relation to value of the assets. The Montecarlo framework is generally used in the market in order to simulate the future movements of an asset (equities; foreign currency rates; interest rates; commodities, etc.) based on the normality property assumed in the returns, and on the implied lognormality that the asset quoted prices have. Some of the inputs required are as follows:

- Annualized volatility of the assets. This volatility may be obtained from the volatility of the equity market value of the entity. If the company's shares are not publicly traded, we can use similar traded companies in order to estimate this input.
- Annualized expected return of the assets.

The Montecarlo method is based on the assumption that an asset value moves with uncertainty in the market, that is to say it is stochastic by nature. However, although an asset is understood to follow a stochastic process, its expected returns and volatility define its expected value and confidence intervals within a given timeframe. The stochastic process that allows an asset movement to be simulated within a given period is also known as a generalized Wienner process, and may be noted as:

$$dS = \mu S dt + \sigma S dZ \tag{4}$$

where S is the asset price; μ is the asset drift (computed as the average annualized return); σ is the instantaneous volatility (standard deviation) at time t for the asset price; and Z is a standard Brownian motion which provides the process with stochastic property and follows a Normal distribution (0,1). The discrete-time version of the model is:

$$\Delta S = \mu S \Delta t + \sigma S\, Z \sqrt{\Delta t} \tag{5}$$

Following Ito's lemma (see Cox and Miller (1977); Brigo and Mercurio (2006); Hull (2012) for instance) and discretizing, we have:

$$\ln(S(t+\Delta t)) = \ln(S(t)) + \mu \Delta t - \frac{\sigma^2}{2}\Delta t + \sigma\left(Z(t+\Delta t) - Z(t)\right) \tag{6}$$

and in terms of the generic asset price jump from t to Δt:

$$S(t+\Delta t) = S(t) e^{\left(\mu - \frac{\sigma^2}{2}\right)\Delta t + \sigma Z \sqrt{\Delta t}} \tag{7}$$

That is, (7) is the equation which defines the asset price movement simulated from t to $t + \Delta t$ based on the annualized asset volatility σ, drift μ, and the stochastic value that Z takes for each simulation jump.

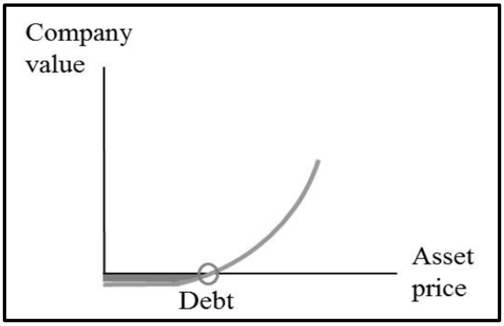
5.2.3. Model theory (II): the company as a call option and the equity-asset relationship

Assuming that the equity price follows the process stated in (6), we can proceed to the next assumption of the model: the company may be viewed as a call option, in the sense that when the assets value decreases below the debt value, the company's value is near to zero. This property is based on the following facts and assumptions:

1) an option price may be simulated following (7), as in the Black-Scholes-Merton option pricing framework,
2) the company assets value is expected to follow the same behaviour as the equity has by (7), that is log-normally distributed, with adjusted annualized volatility and drift. This assumption is consistent since equity movements will impact the asset movements assuming constant liabilities, but the movement proportion will not be the same, hence drift and volatility should be adjusted,
3) debt value is assumed as a constant for the simulated period.

Merton's credit risk model assumes the analogy of a company value (its equity market value) and a call option on its assets value, as Figure 5 suggests:

Figure 5
Company value viewed as a call option



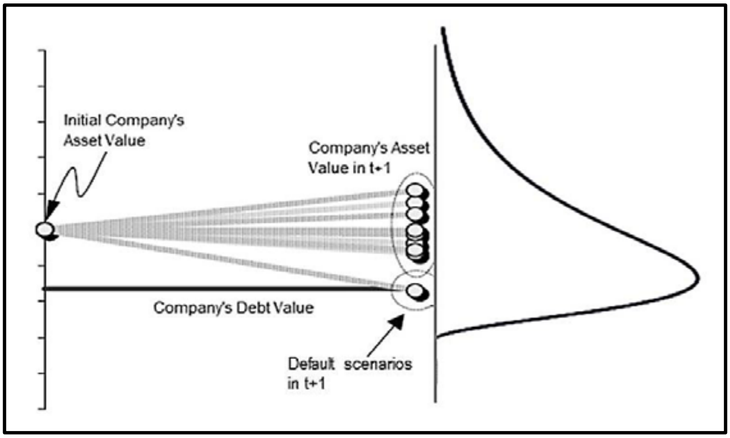
Source: Compiled by the authors.

In the Black-Scholes-Merton framework, an asset's future path can therefore be simulated as in (7), adapting the model inputs on the next asset value diffusion process:

$$V(t+\Delta t) = V(t)e^{\left(\mu - \frac{\sigma_V^2}{2}\right)\Delta t + \sigma_V Z\sqrt{\Delta t}} \tag{8}$$

where $V(t)$ is the company's asset value today; μ is the drift, understood as the asset annualized growth; σ_V is the asset volatility; and Z is a standard Brownian motion. Under this premise, equation (8) may be used to simulate asset pathways over a given timeframe in order to calculate the percentage of simulations that lead the asset price to decrease below the debt book value over a given timeframe (so-called time-to-default, usually one year), so as to obtain the probability of default.

Figure 6
Merton's default model - simulation scheme



Source: Compiled by the authors.

The Black-Scholes-Merton model for option pricing also provides an analytical solution for the simulation framework explained above[15]. A call option value - in this case the company's expected value (equity) depending on contingent underlying (the assets value) - can be calculated. Hence, from the Black-Scholes pricing model, the probability of default may be calculated deriving from (7). The Black-Scholes model defines a call option price as:

$$Call_{European} = S\,\Phi\left(d_1\right) - Ke^{-rt}\Phi(d_2) \qquad (9)$$

where S is the equity price; K is the strike; r is the risk-free rate; and:

$$d1 = \frac{Ln\left(S/K\right) + (r + \frac{\sigma^2}{2})t}{\sigma\sqrt{t}} \qquad (10)$$

[15] See, for example, Black and Scholes (1973) or Hull (2012) with regard to obtaining the analytical solution from the generalized Wienner process.

$$d2=\frac{Ln\left(S/K\right)+(r-\frac{\sigma^2}{2})t}{\sigma\sqrt{t}}=d1-\sigma\sqrt{t} \tag{11}$$

Hence in the case of a company's expected value, the above equations become the following:

$$Equity\,value=V\,\Phi\left(d_1\right)-De^{-\mu t}\Phi(d_2) \tag{12}$$

$$d1=\frac{Ln\left(V/D\right)+(\mu+\frac{\sigma^2}{2})t}{\sigma\sqrt{t}} \tag{13}$$

$$d2=\frac{Ln\left(V/D\right)+(\mu-\frac{\sigma^2}{2})t}{\sigma\sqrt{t}}=d1-\sigma\sqrt{t} \tag{14}$$

As explained by, among others, Nielsen (1992) and Hull (2012), $\Phi(d_2)$ is the analytical solution for the probability of an asset price being higher than the strike price; that is, the probability of exercising the option. In (14) $d2$ is the Asset *Distance to Default* in number of standard deviations. $\Phi(d_2)$ is therefore the probability of being higher than the strike price, in this case the debt book value. In other words,

$$\Phi\left(d_2\right)=Survival\,Probability \tag{15}$$

Hence,

$$1-\Phi\left(d_2\right)=Default\,Probability \tag{16}$$

When using and calibrating models such as (8) and (16), two factors are critical by nature: the company's assets growth and asset volatility. The company's assets growth represents the average return expected for the assets, hence the higher the drift, the higher the expected asset value and, therefore, the lower the default probability. It may be estimated as the assets' annualized return over the last 5 years. Regarding asset volatility, it is clear that it is a factor not observable as such, and it is not wholly reliable given the frequency with which financial statements are issued. However, as previously described, asset volatility is affected by equity volatility. Hence, we need to identify the value of asset volatility given by the equity volatility: this calculation relies on the Black-Scholes differential equation:

$$rf=\frac{\partial f}{\partial t}+rS\frac{\partial f}{\partial S}+\frac{1}{2}\sigma^2S^2\frac{\partial^2 f}{\partial S^2} \tag{17}$$

where f is the derivative price on a contingent underlying S which follows the stochastic process (5), and r is the risk-free rate. (17) can be approximated by a Taylor series expansion which gives us:

$$\Delta f = \frac{\partial f}{\partial t}\Delta t + \frac{\partial f}{\partial S}\Delta S + \frac{1}{2}\frac{\partial^2 f}{\partial S^2}\Delta S^2 + \frac{1}{2}\frac{\partial^2 f}{\partial t^2}\Delta t^2 + \frac{\partial^2 f}{\partial S \partial t}\Delta S \Delta t + \ldots \tag{18}$$

(18) states the relationship between the price of the derivative and the risk factors involved in its pricing. The first term on the right-hand side states how much the derivative price changes for a change in a time unit. This partial derivative is known as Theta (Θ). The second term, Delta (Δ), relates the derivative price change to the underlying price change. The third term, Gamma (Γ), is the second partial derivative of the derivative price with respect to the underlying price, in order to capture the convexity effect, as can be seen in Figure 5. Subsequently, additional and cross-partial derivatives can be computed. If we ignore the Theta term, option price change may be understood as follows:

$$\Delta f = Delta\,\Delta S + \frac{1}{2} Gamma\,\Delta S^2 \tag{19}$$

Hence we are able to establish the relationship between asset and equity volatility absolute quantities as:

$$\sigma_{equity} Equity_{t_0} = \Delta_{Eq|V}\,\sigma_V V_0 + \frac{1}{2}\Gamma_{Eq|V}\,\sigma_V V_0^2 \tag{20}$$

where σ_{equity} is the historical or implied annualized equity market price volatility; $Equity_{t_0}$ is the company's equity market price at the moment of calculation; $\Delta_{Eq|V}$ is the delta of the Equity on the company's assets; $\Gamma_{Eq|V}$ is the gamma in the same context; V_0 is the company's assets value; and σ_V is the asset volatility to be calibrated. Knowing that the Black-Scholes framework gives the following on European options,

$$Delta_{call} = \Phi(d_1) \tag{21}$$

$$Gamma_{call} = \frac{\Phi(d_1)}{S_0 \sigma \sqrt{t}} \tag{22}$$

we may calibrate the σ_V by rearranging the terms in (20), and obtain the volatility to be used in (8) and (14).

5.2.4. Model implementation: from default probabilities to short-term Credit Ratings and additional considerations

Following the Reuters database, the table below relates the 1 year probability of default and the rating letter assigned:

Table 6
Implied 1y Probability of Default & Rating

Probability of Default (Lower Limit)	Probability of Default (Upper Limit)	Implied Letter Rating
0,0000%	0,0010%	**AAA**
0,0010%	0,0020%	**AA+**
0,0020%	0,0040%	**AA**
0,0040%	0,0080%	**AA-**
0,0080%	0,0150%	**A+**
0,0150%	0,0250%	**A**
0,0250%	0,0380%	**A-**
0,0380%	0,0540%	**BBB+**
0,0540%	0,0730%	**BBB**
0,0730%	0,1110%	**BBB-**
0,1110%	0,1870%	**BB+**
0,1870%	0,3060%	**BB**
0,3060%	0,4720%	**BB-**
0,4720%	0,8700%	**B+**
0,8700%	1,5600%	**B**
1,5600%	2,5000%	**B-**
2,5000%	3,6900%	**CCC+**

Source: Reuters, compiled by the authors.

Among the issues to be considered when implementing this model are the following:

1) Entities are generally more likely to default when their asset value reaches a certain critical level somewhere between the value of total liabilities and the value of short-term debt. In practice, therefore, using only the short-term debt or the total liabilities as a strike may not be an accurate measure of the actual probability of default. The strike selection will also depend on the debt structure and the leverage ratio sensitivity, among other factors. However, a widespread solution is to set the strike - the so-called Default Point (DPT) - as follows:

$$DPT = Short\,Term\,Debt + 0.5\,Long\,Term\,Debt \qquad (23)$$

2) In contrast to the Merton concept, the KMV μ is no longer a risk-free rate related return, but the expected rate of the return of the company's asset, that is to say, the relative logarithmic return between $Assets_t$ and $Assets_{t+1}$.

3) The Distance-to-Default equation can be approximated by

$$DD = \frac{\mathrm{E}(V_t) - DPT}{\sigma} \qquad (24)$$

where drift is very low and time-to-default (t) is also short, being $\mathrm{E}(V_t) = V_t\, e^{\mu t}$.

4) Although time-to-default is generally set at 1 year forward, the extension of the model to longer terms is straightforward. The default point, asset volatility, and expected asset value are calculated as before except that they take the longer horizon into account. For example, when calculating the default probability for a 3 year horizon, we need to estimate the total debt and its distribution between the short- and long- terms. It is a conservative assumption that all long-term debt is refinanced by short-term debt, hence expectations on this matter are key. In addition to the changing of the default point as we extend the horizon, our uncertainty regarding the actual asset future value also increases. The expected asset value increases at the expected growth rate (drift), and the total asset volatility increases proportionally to the square root of time.

The example below is presented in order to clarify the model's implementation.

We may assume that following the analysis of a company's latest balance sheet, we have the following information:

- Total Assets: 40,000,000€
- Short-term debt book value: 15,000,000€
- Long-term debt book value: 18,000,000€
- Drift: 0.8% annualized
- Asset volatility already calibrated: 16%
- Time-to-default: 1 year

We consider the *DPT* = 15m € + 0.5*18m € = 24m €

Thus, we use the above information to compute $d2$:

$$d2 = \frac{Ln\left(40/24\right) + (0.008 - \frac{0.16^2}{2})1}{0.16\sqrt{1}} = 3.16$$

So that

$$1 - \Phi\left(d_2\right) = 1 - 99.92\% = 0.078\%$$

Following Table 6, the 1 year default probability leads to an estimated credit rating of BBB-. This is an example of how to use financial and market information within the model. Obviously further financial and accounting analysis is highly recommended in order to accurately set the risk factors within the model. This is to say, there may be certain items which could be adjusted or not considered, such as longest-term debt or hedged positions, for example.

It should be noted that this methodology is useful for obtaining 1 year default probability or, as previously explained, 2 or 3 year cumulative default probabilities once debt value is adjusted based on its expected future structure.

However, in order to build a consistent survival probability curve, the best procedure is to analyze CDS and quoted bond default rate implied curves once the rating is estimated, based on similar companies in terms of rating and sector.

6. CONCLUSIONS

Under IFRS accounting standards, entities must estimate a PD or YTM in several different cases, for example as an input for derivatives CVA/DVA adjustment; as an input for loan loss provisioning under IFRS 9; as a yield for discounting future lease cash flows under the IFRS 16 lessees capitalization model (if the interest rate implicit in the lease cannot be obtained); etc.

When market information (such as quoted CDSs or bonds) is not available and hence cannot be used to obtain the corresponding PD or YTM, the company should develop an internal methodology allowing them to be estimated. This internal methodology must be consistent with the IFRS 13 fair value framework in the sense that it should use as much market information as possible.

We propose two different methodologies that entities can follow in order to obtain a theoretical credit rating of a counterparty which in turn may be used as the first step for estimating the PD or YTM of that counterparty. These methodologies are based in part on previous literature, but are further adapted to accounting requirements and are configured in such a way they may be applied by almost any company.

The first methodology is the Financial Rations Scoring Model (FRS). It is based on analyzing several key financial ratios of the counterparty. The general level of those ratios is compared to the level of the same ratios in other companies (from the same sector and country where possible) that have an official rating issued by a rating agency.

The second methodology is based on the equity value of a company viewed as a call option, in the sense that when the asset's value decreases below the debt value, the company's value is zero or near to zero. This situation is considered to be a credit event, and the probability of its occurrence represents the probability of default that is linked to a credit rating letter.

Both methodologies tend to converge as they implicitly share financial and market inputs. Leverage and coverage ratios are used in the first model as inputs, whereas the second model output *distance-to-default* depends highly on the difference between assets and liabilities. Likewise, the asset volatility and drift used as inputs in the second model are directly related to the liquidity and growth ratios used in the FRS model.

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