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Combining accounting data and a structural model for predicting credit ratings: Empirical evidence from European listed firms

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ABSTRACT

Ratings issued by credit rating agencies (CRAs) play an important role in the global financial environment. Among other issues, past studies have explored the potential for predicting these ratings using a variety of explanatory factors and modeling approaches. This paper describes a multi-criteria classification approach that combines accounting data with a structural default prediction model in order to obtain improved predictions and test the incremental information that a structural model provides in this context. Empirical results are presented for a panel data set of European listed firms during the period 2002–2012. The analysis indicates that a distance-to-default measure obtained from a structural model adds significant information compared to popular financial ratios. Nevertheless, its power is considerably weakened when market capitalization is also considered. The robustness of the results is examined over time and under different rating category specifications.

1. Introduction

Credit ratings are important ingredients of the credit risk management process, and they are widely used for estimating default probabilities, supporting credit-granting decisions, pricing loans, and managing loan portfolios. Credit ratings are either obtained through models developed internally by financial institutions (Treacy and Carey, 2000) or provided externally by credit rating agencies (CRAs). The latter, despite the criticisms on their scope and accuracy (e.g., Frost, 2007; Pagano and Volpin, 2010; Tichy et al., 2011), are widely used by investors, financial institutions, and regulators, and they have been extensively studied in academic research (for a recent overview, see Jeon and Lovo, 2013). In this context, models that explain and replicate the ratings issued by CRAs can be useful in various ways, as they can facilitate an understanding of the factors that drive CRAs' evaluations, provide investors and regulators with early-warning signals and information for important rating changes, and support the credit risk assessment process for firms not rated by the CRAs.

Previous studies have focused on analyzing and predicting credit ratings using mostly firm-specific data (usually in the form of financial ratios) and market variables (Huang et al., 2004; Mizen and Tsoukas, 2012; Pasiouras et al., 2006). Some recent studies (Hwang et al., 2010; Hwang, 2013; Lu et al., 2012) have also considered default risk estimates from structural models (Black and Scholes, 1973; Merton, 1974). Nevertheless, this line of research has been underdeveloped, as no systematic analysis has been conducted to examine the value of the additional information that the estimates of structural models provide compared to accounting-based data for predicting credit ratings, even though considerable research has been done on this issue in the context of default prediction (e.g., Agarwal and Taffler, 2008; Hillegeist et al., 2004; Vassalou and Xing, 2004). Hilscher and Wilson (2013), however, argue that focusing solely on a firm's default risk may lead to considerable loss of information in credit risk assessment, as systematic risk is also an important yet distinct dimension, and it is best modeled through credit ratings. This is in accordance with the results of Das et al. (2009), who found that a combination of accounting variables and a structural model was more powerful in explaining CDS spreads when compared to the independent use of its main components.

Therefore, given the fundamental differences between default prediction and credit ratings and the possible synergies that can be derived through the combination of different credit risk modeling approaches, it is interesting to explore the usefulness of incorporating market-based risk estimates from a structural model to

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the analysis and prediction of credit ratings in combination with financial data and simple market variables, such as capitalization. This type of analysis can provide further evidence on the relationship between credit ratings and default estimates, the added value of structural models in credit risk assessment, the role of their main ingredients, and the synergies between structural and reduced-form models. In this study, we contribute to the literature by exploring these issues using a sample of European companies from different countries over the period 2002–2012. While most of the past studies related to the analysis of the ratings issued by CRAs have focused on the U.S. and the UK, the ratings of firms in European countries (other than the UK) have been relatively under-examined. The focus on European data has some interesting aspects. First, during the past decade, particularly after the outbreak of the European sovereign debt crisis, the role of CRAs has received much attention from authorities, regulators, and governments in Europe. Furthermore, in contrast to U.S. firms, which operate out of a single country, European firms face different economic and business conditions, and the global crisis has not affected all European countries in the same manner. These particular features make it interesting to examine how the findings of studies conducted in other regions and time periods translate into a cross-country European setting, and to investigate the existence of time-varying effects, particularly in light of the ongoing turmoil in the European economic environment.

Except for the above contributions to the literature, on the methodological side we employ an innovative non-parametric multi-criteria decision-making (MCDM) technique, as opposed to the parametric statistical methods (e.g., logistic or probit models) often used in this area. MCDM is well suited to the ordinal nature of credit ratings and the features of credit scorecards, while taking into account the nonlinearities observed in previous studies (Hwang et al., 2010; Mizen and Tsoukas, 2012) through an easy-to-comprehend additive modeling form that does not rely on statistical assumptions. In this framework, we introduce a new linear programming approach for building rating prediction models that explicitly take into consideration the multi-grading nature of credit ratings.

The obtained empirical results indicate that a structural model provides significant additional information when combined with traditional accounting-based ratios. However, its significance is considerably reduced when market capitalization is also considered. The analysis of the stability of the results over time further shows that the relative importance of the capitalization of firms has increased during the European sovereign debt crisis. Finally, the obtained conclusions are robust when considering a dichotomic scheme (i.e., investment vs. speculative grades), but the proposed multi-grading MCDM modeling approach is found to be more accurate than dichotomic prediction models.

The rest of the paper is organized as follows. Section 2 discusses the market model used in the analysis, as well as the multi-criteria approach employed for constructing the credit rating classification models. Section 3 is devoted to the description of the data set and the variables, whereas Section 4 presents the empirical framework and the analysis of the obtained results. Finally, Section 5 concludes the paper and discusses some future research directions.

2. Methodology

2.1. Market model

The works of Black and Scholes (1973) and Merton (1974) led to the development of the research on structural models for credit risk modeling. In this framework (henceforth referred to as BSM), a firm is assumed to have a simple debt structure, consisting of a single liability with face value L maturing at time T. The firm defaults on its debt at maturity if its assets' market value is lower than L. In this context, the firm's market value of equity (E) is modeled as a call option on the underlying assets (A), whose value is given by the Black–Scholes option pricing formula:

$$E = A\mathcal{N}(d_1) - Le^{-r_f T}\mathcal{N}\left(d_1 - \sigma\sqrt{T}\right) \tag{1}$$

where r_f is the risk-free rate, σ is the volatility of the asset returns, $\mathcal{N}(\cdot)$ represents the cumulative normal distribution function, and

$$d_1 = \frac{\ln(A/L) + (r_f + 0.5\sigma^2)T}{\sigma\sqrt{T}}$$

Furthermore, under Merton's assumption that equity is a function of assets and time, the following equation is derived from Itô's lemma (Hull, 2011):

$$\sigma_E = \frac{A}{E}\sigma\mathcal{N}(d_1) \tag{2}$$

Solving Eqs. (1) and (2) simultaneously or with iterative procedures (Hillegeist et al., 2004; Vassalou and Xing, 2004) leads to an estimate of the market value of assets (A) and the volatility of the assets' return (σ). Then, a distance-to-default (DD) measure can be defined as the number of standard deviations that the firm is away from default (i.e., how much $\ln(A/L)$ should deviate from its mean in order for default to occur; Vassalou and Xing (2004)):

$$DD = \frac{\ln(A/L) + (\mu - 0.5\sigma^2)T}{\sigma\sqrt{T}} \tag{3}$$

where μ is the expected return on assets, which can be estimated from the annual changes in A obtained from the solution of Eqs. (1) and (2).

Despite its simplicity and appealing grounding in financial theory, the basic BSM model is based on some well-documented but strong assumptions (Agarwal and Taffler, 2008; Bharath and Shumway, 2008), most notably involving the simple structure of a firm's debt (e.g., it is assumed that a firm issues a zero-coupon bond of maturity T, and that default only occurs at maturity) and the statistical distribution of the firm's assets' value (it is assumed that it follows a geometric Brownian motion, thus implying that assets' value is log-normally distributed). Nevertheless, the model has attracted much interest among academics and practitioners, and several variants have been introduced in the literature (see Agarwal and Taffler, 2008 for a comparative analysis).

2.2. Multi-criteria analysis approach

In this study, the development of models to explain and predict credit ratings is based on a non-parametric MCDM approach. MCDM has evolved into a major discipline in operations research involved with decision problems under multiple criteria, and has been extensively used in various areas of financial risk management (Zopounidis and Doumpos, 2013), including credit scoring and rating (Doumpos and Pasiouras, 2005; Doumpos and Zopounidis, 2011). In this context, we introduce and employ a variant of the UTADIS multi-criteria classification method (Doumpos and Zopounidis, 2002) in order to cope with the multi-class nature of credit ratings. The adopted MCDM approach is based on the construction of an evaluation (scoring) model expressed in the form of an additive value function, which is widely used by financial institutions for credit scoring and rating (Krahnen and Weber, 2001):

$$V(\mathbf{x}_i) = \sum_{k=1}^{K} w_k v_k(x_{ik}) \tag{4}$$