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Factors of Credit Ratings for Transfer Pricing of Loans in European Conditions

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Abstract

In accord with international transfer pricing regulations, the borrower's creditworthiness is the main factor to be reflected in valuation of cross-border loan transactions between associated enterprises. However, trouble invariably arises for small and medium-sized enterprises that do not have an assigned credit rating. The aim of this paper is to determine the most reliable predictors of a company's credit rating for European entities facing missing rating coverage for the purpose of transfer pricing. Based on 2015–2019 data sourced from the Orbis database, the study examines key financial ratios and non-financial information that could be instrumental in reconstructing a long-term rating category of a company assigned by Moody's Investors Service. The results identify interest coverage as the most useful predictor. Therefore, a law-approved and tax-acceptable approach to pricing of financial transactions between unrated parties (*i.e.,* without credit rating) should preferably exploit interest coverage as a link to the otherwise missing ratings.

Keywords: Transfer pricing, credit ratings, predictors of creditworthiness, interest coverage, European companies.

JEL Classification: C51, H21, H25, H26, H70

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1. Introduction

In the past few decades, transfer pricing as the practice of generating prices between associated enterprises that are under common ownership and control has received immense attention among scholars of international management and corporate finance and regulatory bodies (Kumar *et al.*, 2021). A common denominator that incites an interest in transfer pricing is that enterprises within integrated structures are not motivated to assign a market price to their mutual transactions, but rather face strong incentives to avoid or downplay the market mechanism (Davies *et al.*, 2018). Whereas the former interest group studies aspects of transfer from functional, economic, strategic and organizational viewpoints (*e.g.*, Rossing and Rohde, 2014), the latter group pursues societal interests by preventing unethical and illegal practices oriented on cross-border profit shifting, tax reduction, tax avoidance or accounting adjustments. These efforts then synthesize into regulatory guidelines the purpose of which is to induce or emulate a market mechanism between associated entities. The bibliometric survey by Kumar *et al.* (2021) outlines seven major fronts of academic research in transfer pricing ranging from tax policy issues to organizational and process-oriented aspects, but what is absent is the study of technical aspects that facilitate setting of prices in particular conditions that often surface in practical applications. This paper focuses on one issue that emerges in pricing of loans between associated corporate entities. In such a case, transfer pricing instructs to find an appropriate interest rate that would be close to an interest rate negotiated under common market conditions between independent entities.

Regarding pricing of loan contracts between associated entities, Transfer Pricing Guidance on Financial Transactions[1] (OECD, 2020, para 10.62) prescribes that the creditworthiness of a borrower is one of the key factors in determining the interest rate to charge. Credit ratings serve as a useful measure of creditworthiness, which contributes to the identification of potential comparable transactions or the application of economic models in relation to associated party transactions. A publicly available credit rating assigned by an independent credit rating agency is deemed acceptable and sufficiently informative to map the rating class onto market interest rates applied to traded instruments. Nonetheless, most enterprises do not have publicly available credit ratings, and they are allowed to apply quantitative and qualitative analyses to approximate or replicate the credit rating by using publicly available financial tools or published credit rating methodologies.

With a focus on European conditions, this paper intends to assist the process of finding approximate or replicate credit ratings for borrowers whose official credit ratings published by

1 This Guidance was incorporated as Chapter X into the OECD Transfer Pricing Guidelines for Multinational Enterprises and Tax Administrations in 2022, during its updates. Hereinafter, OECD Transfer Pricing Guidelines. For more details: https://doi.org/10.1787/0e655865-en

independent rating agencies are not available. In this situation, the borrowing enterprise can only rely on a limited sample of quantitative and qualitative information. The idea is to use such financial and possibly also qualitative predictors that are most closely associated with publicly available credit ratings and instrumental in their reconstruction.

More specifically, the aim of the paper is to determine the most reliable predictors of a credit rating for European companies whose rating marks are unavailable. The reason is that credit ratings are available, with a few exceptions, only for a handful of large European companies with international business engagement, while some countries are almost completely unrepresented in corporate rating analyses. An example is Central and Eastern European countries. This paper makes use of long-term rating marks assigned by Moody’s Investors Service and sourced from the Orbis database and confronts them with a variety of indicators. The available sample size for which ratings could be extracted from the popular and extensive Orbis global database counts less than 1,000 European companies, which merely proves that the task of pricing loan contracts based on credit ratings would leave most European companies in the dark and uncertainty.

To overcome a crucial obstacle that arises in the practice of transfer pricing, the paper explores the possibility of replicating a credit rating using a single financial ratio. Specifically, the analysis identifies key financial ratios or additional non-financial information that could be instrumental in reconstructing a rating category of a company in pricing its financial transactions. The study employs data sourced from the Orbis database in March 2022 for a total of 913 entities located in the European Union (EU-27) and the United Kingdom over the period between 2015 and 2019. The findings favour interest coverage as a financial ratio that is most closely associated with Moody’s long-term ratings.

The rest of the paper is structured as follows. Section 2 focuses on the rationale of the study and outlines related elements of credit ratings research and methodologies. Sections 3 and 4 give a brief description of the methodology and the available data, respectively. Finally, Section 5 presents the results, and Section 6 concludes key results.

2. Credit Ratings and Their Use in Transfer Pricing

Credit ratings are opinions on the creditworthiness of a corporate issuer, security or liability based on quantitative and qualitative analysis. They derive from an assessment of estimated loss coverage through current and forward-looking measures that capture the borrower’s (or issuer’s) ability and willingness to pay final obligations (including principal, interest, dividends or other types of cash distributions) under the terms of an obligation. The OECD Transfer Pricing Guidelines (OECD, 2022, Chapter X) place a particular emphasis on the use and determination of credit ratings as well as on the influence of group membership (so-called “implicit support”) and how this support should be included and considered in the analysis of a financial transaction. Thus, different options may express the principle of an independent relationship, ranging from a stand-alone, *i.e.*, the rating of the borrower as an independent entity, to a group rating, *i.e.*, the rating of the group in its entirety (Heggmair *et al.*, 2020).

The borrower's credit rating can also be determined internally according to procedures published by rating agencies, *e.g.*, by the methodology of Moody's Investors Services, Fitch Ratings or Standard & Poor's Global Ratings. Gabelle (2021) highlighted available jurisprudence on the use of methodologies for compilation, or credit rating estimates. He pointed out the decision of the French Administrative Supreme Court (Conseil d'État), which acknowledged that the assessment provided by a commercial software product using the company's financial statements for several years is following the OECD regulations (OECD, 2022, Sections 10.72–10.75) that permit explicitly the use of software tools. This ruling is critical in explaining the role of expert modelling of ratings and invites a more creative approach in situations when a credit rating is absent. In some countries, when setting a transfer price, it is mandatory to also consider the financial position represented by the borrower's financial ratios and operational performance (*e.g.*, FR: SNC Siblu case, 2019).

Rating agencies do not only publish simple ratings, but also provide evaluative reviews and regularly update their outlooks (*e.g.*, Bannier and Hirsch, 2010; Driss *et al.*, 2019). In addition to an informative role, credit ratings also have an important economic function as they motivate lower-rated borrowers under pressure to refrain from risk-increasing actions. Credit rating may also have direct implications for transfer pricing itself since some states apply safe harbours that unburden bureaucratic procedures in transfer pricing depending on the assessment of the borrower's credit rating (Ištok *et al.*, 2022).

In their survey, Hertikasari and Artha (2022) provided an overview of approaches that are adopted for credit rating determination, and reviewed variables that are related to credit corporate ratings. Hájek and Michalak (2013) highlighted that US rating methodologies are based primarily on company size and the market value ratio, while European methodologies rely more on profitability and leverage indicators. Having inspected Chinese corporate ratings, Gai *et al.* (2022) concluded that current credit rating methodologies overemphasize the role of total assets, but largely ignore the corporate debt burden and company profitability.

Nonetheless, since the world's Big Three on the ratings market (Moody's, Fitch and Standard & Poor's) are all located in the USA, where most global credit rating know-how is concentrated, it is not surprising that credit ratings are primarily assigned to US companies (Brauers and Lepkova, 2019). All efforts to create a large rating agency in Europe have failed, and the three largest US rating agencies dominate even in Europe. However, it may not matter whose ratings are used.

For instance, Brauers and Lepkova (2019) compared credit rating marks assigned by Moody's, Fitch and Standard & Poor's to find out that there are no significant differences between them. If apparently convenient, this statement may not be universally valid since contrary evidence has been provided as well, *e.g.*, by Afonso and Albuquerque (2018) or Frydrych (2021). In some applications, Moody's ratings are favoured. For instance, Hull (2020) argued that Moody's A3 rating is the most frequently targeted optimal rating required by growth stage companies.

Some differences have been observed in the choice of factors on which credit rating methodology is based as inputs. Chodnicka-Jaworska (2018) emphasized that factors used for determination of ratings of European banks differ between small and large rating agencies. The former attach more importance to individual financial conditions, whereas the latter base ratings especially on macroeconomic conditions or general societal trends such as sustainability awareness, political uncertainty (Attig *et al.*, 2021) or even business fluctuations (Edirisinghe *et al.*, 2022).

An exclusive position among individual, company-specific factors associated closely with credit rating is attributed to capital structure. The role of debt service is also fully reflected in Damodaran's methodology, which belongs to the most frequently used approaches in corporate practice. Damodaran (2002) proposed a method to estimate a synthetic rating based on the interest coverage ratio. Despite its utter simplicity, Damodaran (2012, pp. 215–216; 2023) continues recommending his approach to synthetization of rating. Damodaran's current methodology, which is available updated on his personal web page (Damodaran, 2023), derives the credit rating from a single indicator, the interest coverage ratio observed for the current year. The methodology converts the value of interest coverage according to a set of intervals into a rating category for three different groups of companies. Damodaran's approach is often criticized because the credit rating is based on only one indicator, and at the same time calculated from US data, which may question its use in European conditions. However, the role of leverage has been confirmed in several studies, possibly related with tax considerations. For example, Goebel and Kemper (2022) investigated the relationship between capital structure and credit rating changes. They found that rating changes (notch up or notch down) are not automatically associated with a lower level of debt or a more significant debt reduction. The results of their analysis are not in line with Kisgen (2006), who found that companies with a positive change in the capital structure automatically have a higher chance of improving the rating. Tang and Li (2021) found that investors do not react to information related to future rating changes, but only react to the change itself. Moreover, the credit rating downgrade is more obvious for entities having subsidiaries in tax havens (Li *et al.*, 2022).

Non-financial company-specific information may take different forms, such as the life cycle of companies (Blomkvist *et al.*, 2021), brand equity (Hasan and Taylor, 2022), accounting conservatism (Lim and Mali, 2015), financial statement readability (Hsieh, 2022), corporate governance (Dang *et al.*, 2022) or earnings management (Alissa *et al.*, 2013).

There are several rating agencies with proprietary methodologies whose credit ratings are broadly accepted without bearing the burden of proof in transfer pricing. The most prominent methodologies are those of the Big Three, *i.e.*, Moody's (2021), Standard & Poor's (2019) and Fitch (2020). They all apply quite extensive and include philosophies, methods and approaches, evaluation criteria, standard quantitative and qualitative indicators, implicit and explicit support within the group and credit rating scales (long-term and short-term rating).

The methodology of Moody's Investor Service is among the tools often used in practice (*e.g.*, in expert opinions) or in relevant literature (*e.g.*, Pletz *et al.*, 2022). Following the current methodology of Moody's (2021), determination of a stand-alone credit rating reflects sales (revenues), business profile (demand characteristics, competitive profile), leverage and coverage (EBITDA[2], EBITA[3] to interest, retained cash flow to net debt) and financial policy.

There is also a role for qualitative indicators such as information related to management, market and industry (profitability, competitiveness, stability, regulations and industry specifics), aspects of intangible assets, number of employees, suppliers and customers (percentage representation and dependency testing), owner rating, number of owners, product, performance capacity, blocking of transaction accounts, court decisions and tax arrears.

In credit analyses performed by banks in assessments of corporate loan applications, an emphasis is placed on the debt service coverage ratio (DSCR)[4]. The DSCR considers available funds in the numerator with contractual obligations in the denominator for a given year. The importance of the DSCR for determination of credit rating can be comparable to the interest coverage in Damodaran's methodology and the modified *Z*-score for Altman's method of scoring bonds in emerging markets (Altman, 2005). Another key indicator in the provision of loans by commercial banks is the solvency ratio (defined in Table 2). In the case of quick credit analyses, a generally accepted recommendation is to grant the company a bank loan if the solvency ratio is 20% at least (Merjavý, 2022).

2 EBITDA – earnings before interest, taxes, depreciation and amortization charges.

3 EBITA – earnings before interest, taxes and amortization charges.

4 DSCR is defined as: (Earnings after taxes + Depreciation and Amortization charges) / (Interest paid + Principal repayment).

3. Methodological Notes

The methodological aspect of the analysis mostly depends on familiar analytical tools that are common in financial analyses (such as graphical exploratory analysis and association analysis). However, one component deserves a brief review. Specifically, the links between Moody's long--term rating and a variety of financial ratios are measured and described through ordinal regression with an expectation that they may turn out jointly useful in reconstructing rating marks. This element is introduced in this section.

The ordinal character of rating categories avoids use of traditional statistical approaches, such as traditional regression analysis. On the one hand, rating categories are nominal and are not represented by numeric measurements; on the other hand, they are ordered by superiority. To exploit this information, ordinal regression is employed. The main idea is to introduce a sequence of latent numeric variables that arise as a linear combination of various indicators of financial and non-financial information fulfilling the role of predictors, and to map it onto the ordinal rating categories. The model used for this purpose is known as logistic ordinal regression, the proportional-odds model (McCullagh, 1980) or cumulative link model (Christensen, 2019). A detailed textbook exposition is given, *e.g.*, in Harrell (2015).

The model assumes that there are m rating categories (with $m \geq 2$) and the classification is based on k numeric predictors. These predictors may arise by transforming a nominal variable into a set of dummy variables or may include transformations, such as squares or logarithms of other variables. These predictors will be represented by a vector $\boldsymbol{x}$ and will be instrumental in setting up the latent variable ξ for each rating category. Latent variables for individual categories will differ in the coefficients of their definitional linear combinations. A rating category i will have a category-specific intercept α_i and a vector of slopes $\boldsymbol{\beta}$ shared with other categories. Therefore, the latent variable for this rating category will arise as $\xi_i = \alpha_i - \mathbf{x'\beta}$, and will capture indirectly the probability that a company with response x comes from the category i or one that precedes it ordinally. This probability will be denoted as $P\{C \leq i \mid \mathbf{x}\}$, where C denotes the category ordinal number. The model employs the logit transformation to link the probability of assigning a company into a specific category with the observed values of predictors. The model presumes for categories i, $i \in \{1, ..., m-1\}$, the following representation:

$$\text{logit}(P\{C \leq i \mid \mathbf{x}\}) = \xi_i = \alpha_i - \mathbf{x'\beta} \tag{1}$$

or

$$P\{C \leq i \mid \mathbf{x}\} = exp(\xi_i)/(1 + exp(\xi_i)) \tag{2}$$

The logit transformation in (1) is defined as $\text{logit}(x) = \log(x/(1 - x))$, and its inverse is the logistic function that appears in (2). It is worth noting that the model has category-specific intercepts $\alpha_1, \ldots, \alpha_m$, and the identical vector of slopes $\boldsymbol{\beta}$, which is implicitly assumed to be category-independent. By inverting the logarithm on both sides of (1), the left-hand side gives the odds of a company with predictors x being assigned to the category i at most, *i.e.*, $P\{C \leq i \mid \mathbf{x}\}/(1 - P\{C \leq i \mid \mathbf{x}\})$, which explains the interpretation of the regression parameters. Since the last category $i = m$ the probability expression in the denominator is $1 - P\{C \leq m \mid \mathbf{x}\} = 1 - 1 = 0$, the parametric representation in (1) is only adequate for $i \in \{1, ..., m - 1\}$. The parameters are estimated by the maximum likelihood method.

The model has two basic uses: prediction and explanation. The former use is based on estimating probabilities that a company corresponds to individual rating categories. For each rating category, the probability of a company with predictors $\mathbf{x}$ is estimated by using formula (2) with maximum likelihood estimates of the parameters plugged in. For $i = 1$, the probability is simply the first cumulative probability, *i.e.*, $\text{est.}P\{C = 1 \mid \mathbf{x}\} = \text{est.}P\{C \leq 1 \mid \mathbf{x}\}$. For other categories i, $i \in \{2, ..., m - 1\}$, the probability is the difference of cumulative probabilities for two successive categories, *i.e.*, $\text{est.}P\{C = i \mid \mathbf{x}\} = P\{C \leq i \mid \mathbf{x}\} - P\{C \leq i - 1 \mid \mathbf{x}\}$. The last probability $\text{est.}P\{C = m \mid \mathbf{x}\}$ is estimated in a complementary fashion. The prediction seeks to maximize this probability. The latter use is of interest here, and the aim is to identify, with some tolerance for uncertainty, the factors that are most instrumental in explanation of "simple" rating categories.

4. Data

The analysis is based on data sourced in March 2022 from the Orbis database provided by Bureau van Dijk, a major publisher of business information associated with Moody's Analytics. The search focused on active companies located in the European Union (EU-27) and the United Kingdom having available credit ratings and resulted in a dataset of 913 entities over a period of five years from 2015 to 2019. These companies are all privately owned with known credit rating and financial information available for at least one of the selected years. However, there was also a lack of data for several companies. To overlap this issue, we focus on company-year data availability. After dropping company-years with lack of data, the effective sample counted a total of 2,322 company-years.

Table 1: Original and simplified ratings in sample

Grade	Original rating	Company-years	Simplified rating	Company-years
Investment grade	**Aaa**	8	**Aaa**	8
	Aa1	13	**Aa**	62
	Aa2	20		
	Aa3	29		
	A1	66	**A**	388
	A2	117		
	A3	205		
	Baa1	288	**Baa**	777
	Baa2	259		
	Baa3	230		
Speculative grade	**Ba1**	127	**Ba**	400
	Ba2	127		
	Ba3	146		
	B1	190	**B**	628
	B2	304		
	B3	134		
	Caa1	41	**Caa**	56
	Caa2	10		
	Caa3	5		
	Ca	2	**Ca**	2
	C	1	**C**	1

Source: Authors' own elaboration

A crucial limitation of the sample is that the rating categories according to Moody's scale were populated extremely randomly, which becomes more intensified for the study of the distribution across the five-year period. Table 1 displays the distribution of company-years across the Moody's rating scale. Company-years at the end-points of the scale (the best ratings Aaa to A1 as well as the worst ratings Caa1 to C) are represented poorly. To improve the frequencies, the original rating scale was simplified by merging rating categories with subtle differences. Categories numbered 1, 2 and 3 were combined into one simplified category. For instance, groups with Aa1, Aa2 and Aa3 rating marks were merged into one group labelled Aa. In this situation, a total of 13 Aa1, 20 Aa2 and 29 Aa3 company-years passed into a new Aa category of 62 company-years consequently. Whereas this simplification improves the frequencies for the lateral rating categories Aa1 to Aa3 and Caa1 to Caa3, this merging does not help the end-point rating categories Aaa, Ca and C. Nevertheless, keeping these end-point ratings unmerged helps maintain information that the merged Aa rating category is dominated by a better rating Aaa, and that Caa dominates two other rating categories Ca and C. This change of the rating scale in fact replaces the original ordering, the schematic representation of which goes as Aaa » Aa1 » Aa2 » Aa3 » A1 » ... » B3 » Caa1 » Caa2 » Caa3 » Ca » C, by a shorter ordering Aaa » Aa » A » Baa » Ba » B » Caa » Ca » C. The ordinal spirit is fully preserved; however, the scale is thinner, reduced from 21 rating categories to just nine.

The sample extracted from the Orbis database was non-anonymized, and each company was characterized not only by its financial history (financial ratios and Moody's long-term rating) but also identified by some economic and legal facts.

As a first step, the analysis deals with simplified Moody's ratings against financial and non-financial information with an assumption to detect the most useful predictors of Moody's long-term credit ratings. Financial information was represented by 12 financial ratios, which are exhibited in Table 2 below with their definitional formulas and measurement scale. The list of financial predictors encompassed five profitability ratios (ROE, ROCE, three variations of ROS), two leverage ratios (gearing, interest cover), four liquidity ratios (working capital ratio, solvency ratio, current ratio, liquidity ratio) and one efficiency ratio (average days payable). These are the most significant indicators of a company's financial standing, and their selection was also guided by availability of data.

In addition to the 12 financial ratios, three other non-financial predictors were considered, namely country of residence, statistical affiliation with economic activity under NACE Rev 2, and the Bureau van Dijk independence indicator, which identifies associated entities. However, a lack-of-data issue like those noted for Moody's rating marks was again identified. The total of 913 entities in the sample were registered in one of 28 countries and their company-years varied from 1 to 831. Four or fewer company-years were identified in the sample for Bulgaria, Croatia, Hungary, Latvia, Slovakia and Slovenia. The most represented countries with more than 300 company-years were Luxembourg and the United Kingdom. What may be relevant in respect of the geographical residential status of a company is its tax conditions. Among the countries, there are two jurisdictions that are considered tax haven countries (the Netherlands and Luxembourg), and another country (Cyprus) was before the revision of its tax legislation in 2019. Their status is captured by the Corporate Tax Haven Index (CHTI), published in the recent report of the Tax Justice Network (Tax Justice Network, 2021). Since the data sample relates to the period 2015–2019, all these three countries were qualified as favourable tax jurisdictions in this study.

Hence, the country was represented by a dummy variable called *tax haven* (code *TAXHAV*) taking a value of one for companies from the Netherlands, Luxembourg and Cyprus, and zero otherwise. As a result, a total of 373 company-years were for tax haven countries, and the remaining 1,949 company-years were for other countries.

A total of 20 NACE sections were represented in the sample and ranged from 1 company-year (section P) to 370 company-years (section C). To make a more balanced view of the sample and to suppress negligible differences, economic classifications were transformed into a three-level nominal variable *industry* (code *IND*) with three values: soft, "tough" and financial (translatable into a set of two dummy variables). Section K (financial and insurance services) was classified as financial, sections A, B, C, D, E and F (primary and secondary activities) were classified as "tough", and all other sections as soft (non-financial services). As a consequence, the sample contains 509 financial industry company-years, 1,093 soft industry company-years, and 720 "tough" industry company-years.

The independence indicator was available on a 7-level scale (A–, A+, B–, B+, C–, C+, D), where the interpretation for independent entities ensues for the first two grades. This produced a new variable *associated entity* (code *AE*) with a value of 1 for associated entities and 0 otherwise. The sample thus contains 1872 associated entities and 450 independent entities.

Since data compiled from financial statements are known for increased presence of noisy observations and a tendency to anomalous observations, which plagues their further processing and subsequent analysis (*e.g.*, Boďa and Úradníček, 2020), after an initial exploratory analysis, which justified a cautious approach, values of the financial ratios were winsorized (*e.g.*, Blaine, 2018). The winsorization was performed at both tails of the distribution at the 0.05 and 0.95 quantiles, which means that values lower than the 0.05 quantile were reset (censored) to the 0.05 quantile, and values greater than the 0.95 quantile were reset (censored) to this threshold. In consequence, the effect of such observations was reduced.

Table 2: Financial ratios and their definition

Indicator	Code	Definition
Return on equity (%)	*ROE*	$\frac{\text{EAT}}{\text{equity}} \times 100(\%)$
Return on capital employed (%)	*ROCE*	$\frac{\text{EAT + interest paid}}{\text{equity + long-term liabilities}} \times 100(\%)$
Return on sales (EAT-based, %)	*ROS_eat*	$\frac{\text{EAT}}{\text{operating revenue}} \times 100(\%)$
Return on sales (EBIT-based, %)	*ROS_ebit*	$\frac{\text{EBIT}}{\text{operating revenue}} \times 100(\%)$
Return on sales (EBITDA-based, %)	*ROS_ebitda*	$\frac{\text{EBITDA}}{\text{operating revenue}} \times 100(\%)$
Gearing (%)	*GEAR*	$\frac{\text{long-term liabilities + short-term debt}}{\text{equity}} \times 100(\%)$
Interest cover	*ICOV*	$\frac{\text{EBIT}}{\text{interest paid}}$
Working capital ratio (%)	*WCR*	$\frac{\text{working capital}}{\text{total assets}} \times 100(\%)$
Solvency ratio (%)	*SR*	$\frac{\text{equity}}{\text{total assets}} \times 100(\%)$
Current ratio	*CR*	$\frac{\text{current assets}}{\text{current liabilities}}$
Liquidity ratio	*LR*	$\frac{\text{current assets} - \text{treasury shares}}{\text{current liabilities}}$
Average days payable (days)	*AVDP*	$\frac{\text{accounts payable}}{\text{operating revenue}} \times 360$

Note: Profit bases have the following meaning: EAT – earnings after taxes (net income), EBIT – earnings before interest and taxes (before-tax operating profit), EBITDA – earnings before interest, taxes, depreciation and amortization charges (EBIT plus depreciation and amortization charges).

Source: Authors´ elaboration

5. Analysis and Results

A basic statistical summary of the winsorized sample of the indicators considered in the first step of the analysis is provided in Table 3. Information on the simplified ratings is given in Table 1, and non-financial information (*TAXHAV*, *IND*, *AE*) is declared in the preceding paragraph. Table 3 shows that 11 indicators are available for the full extent of 2,322 company-year observations, and only *WCR* has some values missing. The displayed average values create a model company with acceptable to "good" values; however, standard deviations or the differences between average and median values identified a sizeable skewness of the distribution, which would also transpire in a graphical exploration of the sample. This observation simply provides another justification for the adopted winsorization protocol. By conventional standards, even some minimum or maximum values depart from a normal range. Moreover, some of the entities reported a negative net income or a negative amount of shareholders' equity.

Table 3: Basic descriptive statistics of financial ratios

Indicator	Count	Mean	Standard deviation	Median	Minimum	Maximum
ROE	2,322	8.325	16.993	4.201	–21.180	52.441
ROCE	2,322	5.149	4.970	4.738	–1.469	16.302
ROS_eat	2,322	5.670	11.202	0.000	–10.425	36.427
ROS_ebit	2,322	12.559	18.689	4.679	–3.991	63.149
ROS_ebitda	2,322	15.877	20.338	7.736	0.000	66.617
GEAR	2,322	118.201	144.332	71.444	0.000	498.969
ICOV	2,322	2.490	3.798	0.770	–0.629	13.430
WCR	2,093	3.023	6.053	0.000	–4.784	18.702
SR	2,322	23.346	21.034	22.365	–1.748	63.824
CR	2,322	2.336	3.970	1.067	0.000	17.008
LR	2,322	2.115	3.803	0.942	0.000	16.201
AVDP	2,322	29.698	32.505	19.921	0.000	105.223

Source: Authors' own calculations

A graphical investigation was conducted simultaneously to identify how each predictor varies across the simplified rating classes. The distribution of each predictor was compared with the simplified rating classes using a series of stacked boxplots. Nonetheless, to keep the text concise, these plots are not reported here. This approach suggests that companies with a better rating are typically those with higher return on equity and profit margins (EAT and EBIT-based), a higher interest cover ratio, a smaller (even negative) working capital ratio and a higher solvency ratio. This confirms that profitability, sustainability of interest payments as well as liquidity (solvency) are essential for a company's rating status. Whereas these patterns are obvious for most of these financial ratios and the direction of influence, this is not valid for the working capital ratio. Companies with aggressive operating management strategies, as indicated by negative amounts of working capital and negative working capital ratios, are assessed better in terms of their rating. Another obvious feature is a tendency towards non-linear patterns. Indications of inverse U-shaped dependence are visible locally for most of the predictors. A global U-shaped trajectory of average or median values emerges especially for return on capital employed. This suggests that a possibility of non-linear effects should be considered in the process of formal modelling.

A critical aspect of this analysis is the well-known definitional and possibly factual dependence between financial ratios. With regard to definition, there are manifold cross-links among the variables. An opposite example is the du Pont decomposition of return on equity (Boďa and Úradníček, 2016), under which *ROE* is multiplicatively related to *ROS_eat* alongside asset turnover and financial leverage. A company with an excellent profit margin can be expected to yield satisfactory performance for its shareholders. Likewise, there are a total of five profitability ratios. *ROE* and *ROCE* differ both by the profit basis in the numerator and by capital structure, whereas the three versions of the profit margin are different only by their profit bases. Also, *CR* and *LR* are almost identical, and a difference between them may only come up for companies that have acquired their own shares. Table 4 displays a correlation matrix of the 12 numeric predictors in an attempt to confirm or refute these doubts. In computing the reported sample Pearson correlations, all the observations were employed as available. However, in line with the a-priori considerations, *ROE* and *ROCE* are highly correlated (correlation 0.607), and as well EBIT- and EBITDA-based profit margins (correlation 0.649). The correlation coefficient between *CR* and *LR* is 0.981, which only indicates their virtual match, or that only a handful of companies held their own shares. The study of the correlation structure warns against using all these predictors at once for their substitutability and strong statistical association, which could inject a multicollinearity problem into the regression model.

Table 4: Correlation matrix of financial ratios

Correlation coefficient	*ROE*	*ROCE*	*ROS _eat*	*ROS _ebit*	*ROS_ ebitda*	*GEAR*	*ICOV*	*WCR*	*SR*	*CR*	*LR*	*AVDP*
ROE	1.000		–	–	–	–	–	–	–	–	–	–
ROCE	0.607	1.000	–	–	–	–	–	–	–	–	–	–
ROS_eat	0.397	0.421	1.000	–	–	–	–	–	–	–	–	–
ROS_ebit	0.268	0.276	0.554	1.000	–	–	–	–	–	–	–	–
ROS_ebitda	0.174	0.240	0.528	0.649	1.000	–	–	–	–	–	–	–
GEAR	0.046	0.152	0.125	0.092	0.281	1.000	–	–	–	–	–	–
ICOV	0.345	0.497	0.473	0.282	0.351	0.050	1.000	–	–	–	–	–
WCR	0.072	0.168	0.074	−0.067	0.020	0.051	0.262	1.000	–	–	–	–
SR	0.041	0.226	0.228	0.156	0.292	0.047	0.441	0.176	1.000	–	–	–
CR	0.045	0.009	−0.021	0.004	−0.149	−0.088	−0.128	−0.060	−0.058	1.000	–	–
LR	0.037	−0.007	−0.023	0.010	−0.147	−0.087	−0.142	−0.094	−0.078	0.981	1.000	–
AVDP	−0.069	0.095	0.046	−0.029	0.191	0.238	0.191	0.075	0.243	−0.140	−0.145	1.000

Source: Authors' own calculations

The analysis considered both possible non-linearities and mutual links between the 12 financial ratios. The former was reflected by adding square terms to the regression relationship given by Equation (1), while the latter was accounted for by excluding terms that might be statistically correlated or internally co-dependent. The regression specification was set by a step-wise procedure considering the three non-numeric predictors, the 12 financial ratios plus year dummies to control for possible time effects. A bidirectional search algorithm combining backwards and forwards steps as appropriate relied on minimization of the Bayesian information criterion (BIC). The search excluded a simultaneous presence of *ROE* and *ROS_eat*, *CR* and *LR*, and allowed only a specific combination of a general profitability ratio (*ROE* and *ROCE*) with a variant of the profit margin (*ROS_eat*, *ROS_ebit*, *ROS_ebitda*). Such an automated search is suitable for explanation since it excludes irrelevant predictors and leaves only predictors that have a satisfactory degree of predictive power.

The selected model is displayed in Table 5 in the format of a conventional regression output. The selected model relies on *AE*, *IND*, *TAXH*, *ROS_eat*, *ROCE*, *LR*, *IC* (in levels and squared), *AVDP*, *SR* and *GEAR*. The estimated parameters are presented in two blocks, intercepts and slopes separately. The estimated slope parameters are presented with statistical significance as well as 95% confidence intervals for multiplication factors that are associated with odds ratios at slopes. For intercepts, it is formally not correct to evaluate statistical significance or examine confidence intervals, so these columns are left blank. All the estimated coefficients are statistically significant at a level of 0.01. Since each of the numeric predictors has different measurement units and is associated with a different location, it is not possible to look at the estimated coefficients directly to assess the size of influence. To make this possible, the ordinal regression model reported in Table 5 was re-estimated with numeric predictors centred to zero mean and scaled to unit standard deviation. In other respects, the specification was left unchanged, and the estimated coefficients are reported as a separate column in Table 5. For all intents and purposes, this standardization operation only affects the point estimates of the intercepts and slopes of numeric predictors.

The results in Table 5 confirm that both financial and non-financial information is material in explaining long-term credit ratings of companies. Negative signs contribute to worse rating marks, whereas positive signs improve the rating class.

- If a company operates as an associated entity, its rating class is on average better than in the case of independent company. On average, in the case of an independent company, the odds of being in a better rating class are 31.7% lower (and with 95% confidence, this reduction is anywhere between 15.5% and 43.1%).
- Operating in a soft or "tough" industry on average improves the rating class. Companies operating in a soft industry have the odds of being in a better rating class 32.3% higher on average than companies operating in a financial industry. For companies in a "tough" industry, the odds are even higher in comparison with financial companies, by 78.2% on average.
- Location of a company in a country with the status of a tax haven seems to exert a harmful effect on average on its rating class. Companies located in the Netherlands, Luxembourg and Cyprus display odds of a better rating class 45.2% lower on average than companies located in another European country. Therefore, localization of the tax residence in one of these countries can be viewed with suspicion and may have a deteriorating effect.
- It is somewhat disturbing that two profitability ratios have opposite signs. Whereas the sign for the profit margin *ROS_eat* tallies with intuition, and the coefficient suggests that an increase in profitability of sales by 1 percentage point inflates the odds of being assigned a better rating class by approximately 3.4%, the sign for *ROCE* is negative. This entails a negative influence of this profitability aspect on the rating class. Nonetheless, the return of capital employed is a ratio of performance of long-term funding, and it may be represented as:

$$ROCE = ROA \times \left(1 + \frac{\text{short-term funding}}{\text{long-term funding}}\right) \times \left(1 + \frac{\text{interest paid}}{\text{EAT}}\right) \times 100(\%) \qquad (3)$$

Equation (3) proves that *ROCE* also incorporates the aspect of the company's reliance on short-term funding relative to long-term funding and the structure of earnings. A company may achieve a high level of *ROCE* not only through a high level of *ROA*, but also by taking on more short-term funding into its capital structure at the risk of operating stability or by a large exposure to credit risk captured by the proportion of interest paid to net earnings. The negative sign for *ROCE*, although prima facie counter-intuitive, may only embody the hidden features of this ratio. It is thus not surprising that higher *ROCE* may have a deteriorating effect on the odds of a more favourable rating.

- Liquidity is found positively associated with rating. Out of two liquidity-related ratios, only the liquidity ratio, which corrects for treasury shares owned, appears in the model. However, the estimated coefficient does not reveal a particularly strong effect. An increase in *LR* by 1, which effectively means an extreme boost in liquidity and impractical to do, is found to improve the odds of being assigned into a better rating class by 7.20% on average.
- The interest cover ratio enters the model in a non-linear fashion, and despite some seeming confusion in interpretation of its effect on rating. Furthermore, this financial ratio has the most intense effect in comparison with the standardized estimated coefficients. The total effect on rating is given by $\partial(0.806IC - 0.179IC^2)/\partial IC = 0.806 - 0.358IC$, which for a company with an average interest cover $IC = 0$ (since these coefficients are for the model with standardized numeric predictors) means 0.806. For a company one standard deviation above an average interest cover with $IC = 1$, this change is 0.448. The highest effect from other financial ratios is for *ROS_eat* with the standardized estimated coefficient 0.371. To break even between *IC* and *ROS_eat*, this would require a company with interest cover at a value of 1.251 standard deviations above average (which is obtained by solving the equation $0.806 - 0.358IC = 0.358$). This also suggests some threshold of saturation. For companies that do not have an excessively high level of interest cover, interest cover is found to play a dominant role in their rating status. However, once this level is exceeded by approximately one standard deviation from average, the profit margin becomes the most important indicator that underlies the rating status.
- Longer trade credit periods are found negatively associated with rating; and the more a company delays its payments for operating purchases made in relation to a normal working capital cycle, the less favourable rating it is prone to receive. However, this effect seems fairly marginal given the fact that an extension of average days payable by one day decreases the odds of being assigned into a better rating class only by about 0.40%, which means that a fortnight-long delay causes a decrease in these odds by about 5.44%.

- Finally, the last two ratios associated with capital structure, *SR* and *GEAR*, are found negatively associated with rating, which is in line with economic intuition. The former of these, the solvency ratio, measures relative importance of equity funding to all funding, whereas the latter, the gearing ratio, measures relative importance of long-term liabilities and short-term financial obligations to equity funding. Both are designed to capture the degree of robustness of capital structure. A high value of *SR* indicates a conservative company with a safe but costly capital structure. In contrast, a high value of *GEAR* suggests that the company may rely heavily on non-equity financing (other than that relates to the operating cycle), which may represent a threat to the stability of financial structure. Again, the estimated coefficients indicate a relatively insignificant influence of these indicators on rating. An increase in the share of equity in financing assets by 1 percentage point decreases the odds of a favourable rating by 0.9% on average, whereas an increase in non-operating non-equity financing relative to equity financing by 1 percentage point induces a reduction of the odds of a better rating class by 0.1% only on average.

To sum up, the estimated model identifies the interest cover ratio as the predictor with the most relevant explanatory power for a company's long-term credit rating. However, this holds only for companies whose interest cover is below average or only within one standard deviation above average. After reaching some threshold, the role of the most influential predictor is taken over by the profit margin ratio and liquidity. The other financial ratios – *ROCE*, *AVDP*, *SR* and *GEAR* – are about of the same relevance when variability is considered, as follows from the standardized coefficients. Therefore, the dominant role in explaining the credit rating is assumed by aspects of capital structure (stability, costs, ability to pay obligations) and moreover non-financial information related to the proprietary connection of the company to other entities, industrial affiliation and country of tax residence.

Table 5: Fitted model

	Estimated α and β		Standard error	Significance	exp(β) with a 95% confidence interval
	Ordinary	Standardized			
Intercepts					
C|Ca	−7.801	−7.971	1.010	–	–
Ca|Caa	−6.701	−6.871	0.595	–	–
Caa|B	−3.692	−3.861	0.194	–	–
B|Ba	−0.705	−0.875	0.148	–	–
Ba|Baa	0.181	0.011	0.147	–	–
Baa|A	1.935	1.765	0.151	–	–
A|Aa	4.076	3.906	0.186	–	–
Aa|Aaa	6.276	6.107	0.381	–	–
Predictors					
***AE* = 1**	0.366	0.366	0.101	0.000	0.693 (0.569–0.845)
IND = soft	0.280	0.280	0.108	0.009	1.323 (1.071–1.635)
ING = tough	0.578	0.578	0.125	0.000	1.782 (1.395–2.277)
***TAXHAV* = 1**	−0.601	−0.601	0.112	0.000	0.548 (0.440–0.682)
ROS_eat	0.033	0.371	0.004	0.000	1.034 (1.025–1.042)
ROCE	−0.056	−0.277	0.010	0.000	0.946 (0.928–0.964)
LR	0.069	0.264	0.011	0.000	1.072 (1.050–1.095)
IC	0.274	0.806	0.040	0.000	1.315 (1.216–1.422)
IC^2	−0.012	−0.179	0.003	0.000	0.988 (0.982–0.993)
AVDP	−0.004	−0.135	0.001	0.002	0.996 (0.993–0.998)
SR	−0.009	−0.198	0.002	0.000	0.991 (0.987–0.995)
GEAR	−0.001	−0.170	0.000	0.000	0.999 (0.998–0.999)

Source: Authors' own calculations

6. Discussion and Conclusions

The study dealt with the capability of 12 financial ratios relevant to corporate financial condition together with additional non-financial information to reconstruct Moody's long-term ratings. This is a topic relevant to both transfer pricing of financial transactions and corporate financial analysis. For both concerned areas of study, the possibility of mapping a particular financial ratio to credit rating has direct and very strong practical implications. On the one hand, this information is valuable in setting an arm's length interest rate for financial transactions under the current OECD Transfer Pricing Guidelines (OECD, 2022). On the other hand, it helps isolate one financial metric for scrutiny whenever the goal of a corporate financial analysis is primarily to assess the credit standing of a company.

The results indicate that interest coverage has the highest predictive power in this respect. This indicator is also the basis on which Damodaran's methodology rests (Damodaran, 2012; 2023). This finding is in line with the results of Hájek and Michalak (2013), who showed that European credit rating methodologies rely heavily on profitability and leverage. As expected, implicit support resulting from group membership (associated entities) increases the probability of assigning a better rating mark. At the same time, in line with expectations and existing studies (*e.g.*, Li *et al.*, 2022), the link to a tax haven (or a country with preferential tax regime) has a negative impact on the rating assigned, *i.e.*, the link to a tax haven increases the probability of assigning a worse rating mark.

A possible limitation of the study is the sole use of Moody's ratings without any consideration of ratings assigned by Fitch or Standard & Poor's. On the one hand, Moody's ratings are most popular in Europe and were the only ratings available for the analysis, even for a few European companies. On the other hand, in the face of some controversies, there is evidence that there is not much difference in ratings assigned by the Big Three rating agencies (Brauers and Lepkova, 2019). Therefore, it might be insightful to repeat the research with Fitch or Standard & Poor's ratings.

For all intents and purposes, the choice of the 12 financial ratios is rather conventional and conservative. There are other indicators potentially useful in reconstructing credit ratings, such as the DSCR, the computation of which requires more information than figures reported on the balance sheet and the income statement. Although the DSCR is an indicator commonly used by commercial banks, its application in relation to the borrower's debt capacity is often mentioned in literature (*e.g.*, Kisgen, 2006) or in existing methodologies of rating agencies (*e.g.*, Standard & Poor's, 2019). However, it is only possible to use it partially as this indicator is restricted (based on its definition) to considering not only the principal and interest of current loans, but also of a potential new loan, which cannot be captured during testing (as the creditor does not only require the borrower to repay the interest, but also to repay the principal itself). Contrary to the use of the DSCR is the finding of Goebel and Kemper (2022), by which a lower level of debt is not automatically associated with credit rating changes.

In addition, we should highlight one aspect of the study not mentioned earlier. Specifically, a possibility of using a synthetic financial measure instead of standalone financial ratios, such as the bankruptcy *Z*-score. It was devised by Altman (1983) and was tested for its predictive capability as its interpretational power across time and has been found compatible for corporate conditions of other countries (*e.g.*, Režňáková and Karas, 2015; Boďa and Úradníček, 2019). Unfortunately, the given results have proven that it is not possible to use Altman's *Z*-score reliably in reconstructing or estimating Moody's long-term ratings.

Provided that the input data sample can be expanded, one possible future direction of research in this area could be the construction of a rating prediction model or methodology that would satisfactorily correspond to rating categories assigned otherwise by a renowned rating agency. Such a model could be implemented in simplified regime or utilised for a safe harbour established for setting the transfer price for loan transactions between associated enterprises. Furthermore, given the diversity of regulations in European countries on transfer pricing that come out of the general OECD Transfer Pricing Guidelines (OECD, 2022), it is obvious that current standards and rules are not fully clear and leave room for uncertainty or some creativity. Owing to the lack of explicit hard-law transfer pricing rules, tax authorities are supposed to be indulgent, which is highlighted in the existing case law of some countries (*e.g.*, CZ: ARGO-HYTOS s.r.o. case, 2021). Anyway, existing established methodologies seem to be at least an appropriate starting point for development and introduction of a qualified credit rating methodology for a company or a group of companies (*e.g.*, Fossati, 2020). Special attention should be paid to the existence of support provided by a group to its members (*cf.* Daba, 2021), which should be fully reflected in a credit rating methodology for transfer pricing.

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References

Afonso, A., Albuquerque, A. (2018) Sovereign credit rating mismatches. *Notas Económicas*, 46, 49–70. https://doi.org/10.14195/2183-203X_46_3

Alissa, W., Bonsall, S. B., Koharki, K., et al. (2013). Companies' use of accounting discretion to influence their credit ratings. *Journal of Accounting and Economics*, 55(2–3), 129–147. https://doi.org/10.1016/j.jacceco.2013.01.001

Altman, E. I. (1983). *Corporate financial distress: A complete guide to predicting, avoiding, and dealing with bankruptcy.* New York: Wiley. ISBN 978-0471087076.

Altman, E. I. (2005). An emerging market credit scoring system for corporate bonds. *Emerging Markets Review*, 6(4), 311–323. https://doi.org/10.1016/j.ememar.2005.09.007

Attig, N., Driss, H, El Ghoul, S. (2021). Credit ratings quality in uncertain times. *Journal of International Financial Markets, Institutions & Money*, 75(11), 1–20. https://doi.org/10.1016/j.intfin.2021.101449

Bannier, C. E., Hirsch, C. W. (2010). The economic function of credit rating agencies – What does the watchlist tell us? *Journal of Banking & Finance*, 34(12), 3049–3079.

Blaine, B. (2018). Winsorizing. In: Frey, B. *The SAGE encyclopaedia of educational research, measurement, and evaluation*. Vol. 1–4. Thousand Oaks: SAGE Publications. ISBN 978-1-506-326153.

Blomkvist, M., Löflund, A., Vyas, H. (2021). Credit ratings and company life-cycle. *Finance Research Letters*, 39(3), 101598. https://doi.org/10.1016/j.frl.2020.101598

Boďa, M., Úradníček, V. (2016). Inclusion of weights and their uncertainty into quantification within a pyramid decomposition of a financial indicator. *Ekonomický časopis*, 64(1), 70–92.

Boďa, M., Úradníček, V. (2019). Predicting financial distress of Slovak agricultural enterprises. *Ekonomický časopis*, 67(4), 426–452.

Boďa, M., Úradníček, V. (2020). Methodology of industry statistics: Averages, quantiles and responses to atypical values. *E&M Economics and Management*, 23(3), 120–137. https://doi.org/10.15240/tul/001/2020-3-008

Brauers, W. K. M., Lepkova, N. (2019). Is credit rating reserved territory for credit rating agencies? A MULTIMOORA approach for European companies and countries. *Technological and Economic Development of Economy*, 25(6), 1259–1281. https://doi.org/10.3846/tede.2019.10722

Chodnicka-Jaworska, P. (2018). *Bank credit ratings – is the size of the credit rating agency important?* UW Faculty of Management Working Paper Series No. 3.

Christensen, R. H. B. (2019). *Cumulative link models for Ordinal regression with the R package ordinal*. [Retrieved 2023-04-28] Available at: https://cran.r-project.org/web/packages/ordinal/vignettes/clm_article.pdf

CZ: ARGO-HYTOS s.r.o. case. (2021). Supreme Administrative Court, 19 December 2022, file No. 2 Afs 66/2021 (ECLI:CZ:NSS:2023:2.Afs.66.2021.59).

Daba, B. T. (2021). Valuation of implicit support from a transfer pricing perspective. *International Transfer Pricing Journal*, March/April, 132– 143. https://doi.org/10.59403/28vengz

Damodaran, A. (2002). *Investment valuation.* 2nd ed. New York: Wiley. ISBN 978-0-471-75121-2.

Damodaran, A. (2012). *Investment valuation.* 3rd ed. New York: Wiley. ISBN 978-1-118-01152-2.

Damodaran A. (2023). *Ratings, interest coverage ratios and default spread*. [Retrieved 2023-04-28] Available at: https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ratings.html

Dang, M., Puwanenthiren, P., Jones, E., et al. (2022). Strategic archetypes, credit ratings, and cost of debt. *Economic Modelling*, 114, 1–18. https://doi.org/10.1016/j.econmod.2022.105917

Davies, R. B., Martin, J., Parenti, M., et al. (2018). Knocking on tax haven's door: Multinational companies and transfer pricing. *Review of Economics and Statistics*, 100(1), 120–134.

Driss, H., Massout, N., Roberts, G. S. (2019). Are credit rating agencies still relevant? Evidence on certification from Moody's credit watches. *Journal of Corporate Finance*, 59(2), 119–141. https://doi.org/10.1016/j.jcorpfin.2016.08.003

Edirisinghe, C., Sawicki, J., Zhao, Y., et al. (2022). Predicting credit rating changes conditional on economic strength, *Finance Research Letters*, 47(B), 1–14. https://doi.org/10.1016/j.frl.2022.102770

Fitch (2020). *Corporate rating criteria effective from 21 December 2020 to 15 October 2021*. New York: Fitch Ratings Inc. [Retrieved 2023-04-18] Available at: https://www.fitchratings.com/research/corporate-finance/corporate-rating-criteria-21-12-2020

Fossati, R. (2020). Should transfer pricing practitioners become credit rating analysts? Practical instructions based on final OECD guidance on financial transactions. *International Transfer Pricing Journal*, September/October, 355–361. https://doi.org/10.59403/2w8ss7v

FR: SNC Siblu case. (2019). Conseil d'État, 18 March 2019, No. 411189 (ECLI:FR:CECHR: 2019:411189.20190318).

Frydrych, S. (2021). Credit ratings of issuers of green debt instruments. *European Research Studies Journal*, 24(4), 172–179. https://doi.org/10.35808/ersj/2570

Gai, S., Mao, X., Liu, M. (2022). The gap between credit rating theory and practice: Evidence from bond issuers in China. *Procedia Computer Science*, 199, 962–968. https://doi.org/10.1016/j.procs.2022.01.121

Gabelle, B. (2021) Credit ratings. In: Bakker, A., Kale, S. *Transfer pricing and intra-group financing. The entangled worlds of financial markets and transfer pricing.* 2nd ed. Amsterdam: IBFD, pp. 73–100. ISBN 978-90-8722-6.

Goebel, J. M., Kemper, K. J. (2022). Credit rating changes and debt structure. *The North American Journal of Economics and Finance*, 59(1), 1–18. https://doi.org/10.1016/j.najef.2021.101558

Hasan, M. M., Taylor, G. (2022). Brand capital and credit ratings. *The European Journal of Finance*, 29(2), 228–254. https://doi.org/10.1080/1351847X.2022.2029751

Hertikasari, A., Artha, B. (2022). Credit ratings: A literature review. *Journal of Business Management Review*, 3(6), 474–485. https://doi.org/10.47153/jbmr36.4102022

Hájek, P., Michalak, K. (2013). Feature selection in corporate credit rating prediction. *Knowledge-Based Systems*, 51(10), 72–84. https://doi.org/10.1016/j.knosys.2013.07.008

Harrell, F. E. (2015). *Regression modeling strategies*, 2nd ed. New York: Springer. ISBN 978-3-319-19424-0.

Heggmair, M. T., Appuhn-Schneider, M., Gresch, H. (2020). *Transfer pricing and financing: What's the arm's length value of money?* WU Transfer Pricing Workshop, 29 October 2020. Vienna: Wirtschaftsuniversität Wien.

Hsieh, Y.-T. (2022). Financial statement readability and credit rating conservatism. *Journal of Corporate Accounting and Finance*, 33, 145–163. https://doi.org/10.1002/jcaf.22531

Hull, R. M. (2020). Credit rating and company value. *Investment Management and Financial Innovations*, 17(2), 157–168. https://doi.org/10.21511/imfi.17(2).2020.13

Ištok, M., Solilová, V., Brychta, K. (2022). Challenges in transfer pricing: A concept of safe harbours for financial transactions. *Financial Internet Quarterly*, 18(4), 23–34. https://doi.org/10.2478/fiqf-2022-0025

Kisgen, D. J. (2006). Credit ratings and capital structure. *The Journal of Finance*, 61(3), 1035–1072. https://doi.org/10.1111/j.1540-6261.2006.00866.x

Kumar, S., Pandey, N., Lim, W. M., et al. (2021). What do we know about transfer pricing? Insights from bibliometric analysis. *Journal of Business Research*, 134, 275–287. https://doi.org/10.1016/j.jbusres.2021.05.041

Li, W., Wang, C., Tan, B. (2022). How do emerging debt market participants recognize company internationalization? Evidence from effects on credit ratings. *Emerging Markets Review*, 53, p. 22. https://doi.org/10.1016/j.ememar.2022.100939

Lim, H., J., Mali. D. (2015). Does conditional conservatism affect credit ratings? An analysis of Korean KRX bond issuers. Korean Corporation Management Review, 22(5), 127–147.

McCullagh, P. (1980). Regression models for ordinal data. Journal of the Royal Statistical Society, Series B (Methodological), 42(2), 109–142. https://doi.org/10.1111/j.2517-6161.1980.tb01109.x

Merjavý, Š. (2022). Úverová analýza skratkou [Credit analysis in a nutshell]. Bratislava: Inštitút bankového vzdelávania NBS [Institute of Banking Education of the National Bank of Slovakia]. Online course held on 10 May 2022.

Moody's (2021). Rating methodology: Business and consumer services. Atlanta (GA, US): Investor Service. [Retrieved 2023-04-18] Available at: https://www.moodys.com/research/Moodys-updates-its-methodology-for-rating-business-and-consumer-service--PBC_1288068

OECD (2020). Transfer pricing guidance on financial transactions: Inclusive Framework on BEPS Actions 4, 8–10. Paris: OECD.

OECD (2022). OECD Transfer Pricing Guidelines for Multinational Enterprises and Tax Administrations 2022. Paris: OECD. https://doi.org/10.1787/0e655865-en

Pletz, A., Kabir, D., Danesi, B. (2022). Pricing loans. In: Lang, M., Petruzzi, R. Transfer pricing and financial transactions. Current developments, relevant issues and possible solutions. Vienna: Linde. ISBN 978-3709411971.

Režňáková, M., Karas, M. (2015). The prediction capabilities of bankruptcy models in a different environment: An example of the Altman model under the conditions in the Visegrad Group countries. Ekonomický časopis, 63(6), 617–633.

Rossing, C. P., Rohde, C. (2014). Transfer pricing: Aligning the research agenda to organizational reality. Journal of Accounting & Organizational Change, 10(3), 266–287. https://doi.org/10.1108/JAOC-03-2012-0017

Standard & Poor's (2019) Corporate methodology: ratios and adjustments. New York: Standard & Poor's Financial Services LLC.

Tang, L., Li, P. (2021). Are investors fixated on credit ratings? Reinterpreting the municipal bond recalibration. Finance Research Letter, 38(1), 1–6. https://doi.org/10.1016/j.frl.2020.101449

Tax Justice Network (2021). The state of tax justice 2021. [Retrieved 2023-03-21] Available at: https://taxjustice.net/reports/the-state-of-tax-justice-2021