Comparing the Credit Default Risk of the Electricity- and Telecom-Industries with DEA

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Abstract

The purpose of this paper is to add evidence to the important question of regulators whether there is a significant difference in the credit default risk of the electricity and the telecom industry. To answer this question, I apply a data envelopment analysis (DEA)-based method that consists of 2 main steps: First, the relative credit worthiness of each firm in a sample of European electricity and telecom enterprises is assessed with a modified slack-based measure of efficiency (SBM) DEA-model. Second, the thus obtained efficiencies of all enterprises in the sample are ranked and a rank-sum test is performed to test the hypothesis that the two groups belong to the same population. The application of this method to the data of 22 electric utilities and 20 telecom service providers led to a clear rejection of this hypothesis so that I can firmly state that the electricity industry is, on average, characterized by a lower credit default risk than the telecom industry.

Keywords: Credit default risk, DEA, AHP, regulation, WACC, cost of capital

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Contents

1 Introduction

A very practical and frequent problem of electricity regulators in the prevalent price-cap regulation regime is an accurate assessment of the cost of capital of the regulated companies in order to be able to prescribe prices that permit the firms an adequate return on their employed capital. To this end, authorities usually calculate the *weighted average cost of capital* (WACC) whose ingredients are, put simply, the distribution of equity and debt and the respective interest rates.

Notions about what level of the WACC is indeed adequate naturally differ, depending on the perspective. Electricity operators often claim that they face the same risk as the telecom industry and should therefore be granted the same risk-adaptation in the calculation of the WACCs. Electricity regulators, on the other hand, dispute that and usually prescribe lower WACCs than telecom regulators[1]. Or as Knieps (2003) puts it (translated from German):

> The higher business risk in the dynamic, competitive telecom-sector compared to the rather stationary, monopolistic sectors of electricity[, water and airports] is acknowledged throughout the British regulatory authorities.

Basically, this view of electricity regulators is based on the following: Inferring from the methodology of the *capital asset pricing model* (CAPM), a few empirical studies[2] have shown that the systematic risk of telecom enterprises is higher than that of electricity enterprises (i. e. telecom enterprises have a higher β). This higher overall systematic risk of the telecom industry implies that its WACC needs to be higher, either because of a higher interest rate for equity or for debt or both (reflecting that the holders of equity and debt have to be compensated for their higher risk exposure).

In practice, regulators in most countries argue that in both industries enterprises can manage their debt in such a way that its cost, i. e. the

[1] cf. Research (2006), where the WACC of the electricity- and the telecom-industries of most European countries can be found (in German only).

[2] A. Damodaran's comprehensive database (`http://pages.stern.nyu.edu/~adamodar`) for example records for the U.S. an average β between 2000-2006 of 0.74 for the electric utilities industry and of 1.49 for the telecom services industry

interest rate, is equal to the risk free rate (i. e. government bonds)[3]. Therefore the higher risk exposure of the telecom industry, indicated by the higher β, is reflected only in a higher supposed interest rate for equity in the WACC whereas the interest rates for debt in both industries are usually supposed to be the same.

In other words: Up to now the prescribed WACCs of the electricity and telecom industries in practically every European country differed solely due to supposed differences in the cost of equity whereas these industries were treated uniformly concerning their cost of debt. Even when leaving aside methodological criticisms of the CAPM-model, this practice can be regarded as a stark simplification, especially when considering the fact that since the imposition of the *BASLE II*-agreement the individual cost of debt is increasingly dependent on the banks' ratings of the respective firm and therefore the default risk they assign to it.

The question that is to be addressed in this paper is therefore whether this simplification of electricity regulators is indeed justified or do systematic differences of the credit default risk of the electricity- and telecom-industry call for a differential treatment concerning their cost of debt.

In order to answer this question I apply the *data envelopment analysis* (DEA) with the following approach: Take a few (simple) risk-relevant financial ratios, categorize them into input- and output-figures and determine whether the firm can achieve bigger outputs with given inputs, thereby indicating a lower credit-default risk, relative to the other firms in the sample. Consequently I perform a *rank-sum-test* to find out whether the electricity industry has a significantly lower default risk than the telecom industry.

Since the problem of evaluating the credit default risk of firms is ultimately the task of a bank's credit scoring system, in what follows, I will provide a brief background of the techniques that are applied in this field and argue why DEA is a suitable extension or alternative to more conventional methods such as *multiple discriminant analysis*

[3]For a discussion of the undesirable consequences of this practice see Bogner and Rammerstorfer (2007).

(MDA).

2 Background: Credit scoring

A bank's decision upon whether or not to lend money to firms and at what price (i. e. the interest rate) is based on a prediction of the risk of the firm's corporate failure, i. e. the credit risk. The bank's internal credit risk models evaluate a potential client's credit risk by assessing his ability to repay. In the last 2-3 decades an extensive literature has emerged on the prediction of business failure and the development of credit scoring systems (cf. Altman (1968), Beaver (1966), Dimitras et al. (1996) or Dimitras et al. (1999) cited in Emel et al. (2003)). Since the client's current financial situation is a very important (but not the only) determinant of corporate failure, financial ratios are amongst the oldest and most popular ingredients in credit scoring. Of course financial ratio analysis has its limitations, amongst which very important ones are the fact that it is difficult to make an unequivocal judgment about whether a particular ratio is "good" or "bad" and that a firm may be good at some ratios and bad in others so that it is difficult to classify it as altogether strong or weak[4] (cf. Emel et al., 2003, p.105).

To overcome these limitations by creating a composite empirical indicator of financial ratios, *discriminant analysis* (DA) was introduced in the late 1960s. Using univariate analysis techniques, Beaver (1966) developed an indicator with financial ratios that best differentiated between failed and non-failed firms (cf. Emel et al., 2003, p. 105). Beaver's univariate approach was later extended and improved by Altman (1968) to the multivariate *multiple discriminant analysis* (MDA). Between the 1960s and the late 1990s researchers attempted to increase the accuracy and success of MDA and developed and applied new techniques for failure prediction such as *logit and probit*-models, *recursive partitioning algorithms* (RPA) based on a binary classification rationale and *decision support systems* (DSS) in conjunction

[4] An overview of the potential and limitations of financial ratio analysis can be found in Weston and Bringham (1993).

with the paradigm of *multi-criteria decision-making* (MCDM) (see Emel et al. (2003, p. 106) for a comprehensive overview of the developments and a literature survey).
From the late 1990s on *data envelopment analysis* (DEA) was introduced to the field of failure prediction as in Troutt et al. (1996), Simak (1997) and Cielen et al. (2004).

2.1 DEA and Credit Scoring

Data envelopment analysis (DEA) as pioneered by Charnes et al. (1979) is a non-parametric method to estimate the efficiency of enterprises. Its popularity stems from the fact that it can specify an efficient frontier without the need for the definition of a production function by laying a convex hull around the empirically available input-output combinations of the players in the sample. Following Farrell (1957)'s pioneering approach, efficiency of the respective enterprise can then, for example, be measured by the distance between the observation and the estimated ideal on the efficient frontier. Mathematically, this is accomplished by formulating for each enterprise a linear program in which the objective function represents the efficiency of the respective enterprise and the constraints stand for the restrictions of the production possibility set.
In the context of credit scoring those financial ratios that should be as small as possible would serve as inputs and those ratios that should be as big as possible would serve as outputs. Moreover, the "efficiency" (a numerical value) of each firm in this environment is equivalent with its credit worthiness relative to the "leaders" (i. e. the firms with the lowest credit default-risk) in the bank's portfolio. Therefore, throughout this paper the expressions "efficiency" and "relative credit worthiness" will be used interchangeably.
DEA has several advantages to the above mentioned parametric approaches: It naturally provides a single measure of performance by simultaneously handling multiple inputs and outputs without making judgments on their relative importance, whereas with MDA, for example, an ultimately arbitrary aggregation of the different ratios is

necessary to achieve such a single measure (cf. Simak, 1997). Furthermore, no specification of a functional form for the input-output correspondences is required (cf. Paradi et al., 2004). Consequently Simak (1997) shows that the DEA approach achieved at least as good results as the existing discriminant analysis based "Z-score" approach and in most cases even outperformed it.

The main reason, however, why I am looking for alternative ways to classify credit default risks is that in this case, i. e. the electricity and telecom industries, I am dealing with huge enterprises that in almost all cases used to be owned by the state until not too long ago and/or are mostly natural monopolists in that they control the essential facility of the network. As a consequence, actual failures hardly ever occur so that the paired sample tests[5] that are used in most of the conventional bankruptcy prediction models are practically not applicable.

Emel et al. (2003) uses a DEA-based methodology to calculate a "credibility score" to of 82 industrial/manufacturing firms in the credit portfolio of one of Turkey's largest commercial banks. They validate their results by regression and discriminant analyses and expert judgments. In what follows, I will develop a DEA-based methodology that is similar to Emel et al. (2003)'s but specifically geared to enable the comparison of the credit risk of the electricity and telecom industries and incorporates expert opinions in a more sophisticated way.

3 The method

In this section I will develop my method that consists of four main aspects:

1. Finding a suitable DEA-model.
2. Identification of suitable financial ratios.
3. Gathering expert opinions about the relative importance of the selected ratios and incorporation into the selected DEA-model.
4. Using the results of the selected DEA-model to compare the

[5] which are based on a data set consisting half of failed and half of nonfailed companies

default risk of the telecom and the electricity industry as a whole with a so-called rank-sum test.

3.1 Finding a suitable DEA-model

The DEA-model I am looking for has to fulfill three main requirements:

(REQ1) Allow for input- and output-maximization simultaneously,

(REQ2) come up with an efficiency-value for each firm that is invariant to the units of measure and

(REQ3) enable the restriction of permissible ratios between the different in- and outputs in the solution.

(REQ1) is necessary to ensure that inputs (in the context of credit scoring those financial ratios that should be as small as possible) and outputs (ratios that should be as big as possible) are treated equally. This requirement disqualifies models such as and kin to the original formulation of Charnes et al. (1979), referred to as the CCR-model, because here a prior choice between input-(minimize inputs with given outputs) or output-orientation (maximize outputs with given inputs) and thus an undesired prioritization has to be made.
Since my in- and outputs will be of different units of measure, (REQ2) is necessary as I need a distinctive efficiency value for each firm in order to be able to perform the rank-sum test later on. Due to this requirement, the main alternative to the CCR-model, the so-called *additive model* (ADD) (cf. Cooper et al., 2000, p. 91), is not applicable in our case.
(REQ3) caters for our aim to include expert opinions in the optimization process in order to impede extreme solutions (i. e. a firm being efficient that is very good at one ratio but very very bad at all the other ratios).
The only model that satisfies (REQ1) and (REQ2) simultaneously is the so-called *slack based measure of efficiency*-model (SBM), as discussed in Cooper et al. (2000, p. 96 f.). To enhance it for (REQ3) as well, it will be modified as described in the next section.

3.1.1 The modified SBM-model

In order to estimate the efficiency of firm o, the following fractional program in λ, s^-, s^+, π and τ is formulated:

$$\begin{aligned} \min_{\lambda, s^-, s^+, \pi, \tau} \quad & \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{io}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_i^+ / y_{ro}} \\ s.t. \quad & X\lambda + s^- - P\pi = x_o \\ & Y\lambda - s^+ + Q\tau = y_o \\ & \lambda \geq 0,\ s^- \geq 0,\ s^+ \geq 0,\ \pi \leq 0 \\ & \text{and } \tau \geq 0 \end{aligned} \tag{SBMm}$$

where x_o and y_o are the in- and output-vectors of firm o, X and Y are the in- and output-matrices of the the entire sample, m is the number of inputs, s is the number of outputs, λ is a vector of weights, s^- and s^+ are the vectors of in- and output-slacks, P and Q are the matrices of in- and output-weight-restrictions and finally π and τ the respective vectors of weights[6].

It is easy to see that an increase in either s_i^- or s_r^+, ceteris paribus, will decrease the objective value ρ, and, indeed, in a strictly, monotone manner. This means, on the other hand, that (REQ1) is satisfied.

Moreover, the objective function value $\rho \in [0, 1]$ for every firm and, since both the numerator and the denominator are measured in the same units for every item in the objective of (SBMm), the objective function value ρ is invariant to the unit of measurement of each input and output item so that (REQ2) is indeed satisfied (cf. Cooper et al. (2000, p. 97) for proofs). Once again: This ρ, the efficiency of each company, is equivalent to its relative credit worthiness in our context.

The matrices P and Q together with their weights π and τ finally ensure that (REQ3) is satisfied, as will be shown in section 3.1.3.

First, however, it will be shown below, how (SBMm) can be transformed into a linear program to make it solvable.

[6]This model is identical with the standard SBM-model apart from the weight-restriction-matrices and their respective weights $P\pi$ and $Q\tau$.

3.1.2 Linearizing the modified SBM-model

Following Cooper et al. (2000, p. 71) I introduce a positive scalar variable t such that

$$t\left(1+\frac{1}{s}\sum_{r=1}^{s}s_i^+/y_{ro}\right)=1.$$

This way I get (matrix notation):

$$\begin{aligned}\min_{t,\lambda,s^-,s^+,\pi,\tau}\quad & \theta=t-s^-\frac{1}{m}x_oI_me_m\\ s.t.\quad & t+s^+\frac{1}{s}y_oI_se_s=1\\ & tx_o-X\lambda-s^-+P\pi=0\\ & ty_o-Y\lambda+s^+-Q\tau=0\\ & t\geq 0,\ \lambda\geq 0,\ s^-\geq 0,\ s^+\geq 0,\ \pi\leq 0\\ & \text{and } \tau\geq 0\end{aligned}\tag{SBMm-t}$$

where I_m and I_s are m- resp. s-dimensional identity matrices and e_m and e_s are m- resp. s-dimensional vectors of ones.
By defining

$$\Lambda=t\lambda,\ S^-=ts^-,\ S^+=ts^+,\ \Pi=t\pi \text{ and } \mathrm{T}=t\tau$$

I further get:

$$\begin{aligned}\min_{t,\Lambda,S^-,S^+,\Pi,\mathrm{T}}\quad & \theta=t-S^-\frac{1}{m}x_oI_me_m\\ s.t.\quad & t+S^+\frac{1}{s}y_oI_se_s=1\\ & tx_o-X\Lambda-S^-+P\Pi=0\\ & ty_o-Y\Lambda+S^+-Q\mathrm{T}=0\\ & t\geq 0,\ \Lambda\geq 0,\ S^-\geq 0,\ S^+\geq 0,\\ & \Pi\leq 0 \text{ and } \mathrm{T}\geq 0\end{aligned}\tag{SBMm-LP}$$

Since $t>0$, the transformation is reversible so that from an optimal solution to (SBMm-LP), $(\theta^*,\ t^*,\ \Lambda^*,\ S^{-*},\ S^{+*})$, the optimal solution to (SBMm) can be derived by

$$\rho^* = \theta^*,\ \lambda^* = \Lambda^*/t^*,\ s^{-*} = S^{-*}/t^*,\ s^{-*} = S^{+*}/t^*.$$

This relatively simple to solve linear program will be the basis of our further calculations. As mentioned above, the matrices P and Q are responsible for restricting the permissible ratios between the different optimal in- and outputs. In what follows, it will be shown how exactly this is accomplished.

3.1.3 Restricting weights

It is necessary to have a look at the dual of (SBMm-LP):

$$\begin{aligned} \max_{u_0,v,u} \quad & u_0 \\ s.t. \quad & u_0 + vx_o + uy_o \geq 1 \\ & -vX - uY \geq 0 \\ & -v \geq -\frac{1}{m} x_o I_m e_m \\ & \frac{1}{s} y_o I_s e_s u_0 + u \geq 0 \\ & vP \leq 0 \\ & uQ \leq 0 \\ & u_0,\ v \text{ and } u \ldots \text{free in sign} \end{aligned} \tag{SBMm-LPdual}$$

where u_0 is a scalar and v and u are the vectors of in- and output-weights that the program chooses to maximize the ratio between out- and inputs.

I am turning to the so-called *assurance-region approach* (AR) (cf. Cooper et al., 2000, p. 152) to achieve that the ratios between the different optimal weights (v^*, u^*) don't exceed pre-determined upper and lower bounds. This can be accomplished by adding the following bunch of constraints to (SBMm-LPdual):

$$\begin{aligned} l_{i,i+j} \leq \tfrac{v_{i+j}}{v_i} \leq u_{i,i+j} \qquad & i \in \{1,\ldots,m-1\},\ j \in \{1,\ldots,m\} \\ L_{i,i+j} \leq \tfrac{u_{i+j}}{u_i} \leq U_{i,i+j} \qquad & i \in \{1,\ldots,s-1\},\ j \in \{1,\ldots,s\} \end{aligned}$$

where the different ls and us (Ls and Us) are the pre-determined lower- and upper bounds[7] of the various ratios between the different inputs (outputs).
It is easily verified that this is equivalent to setting

$$P = \underbrace{\begin{pmatrix} l_{12} & -u_{12} & l_{13} & -u_{13} & \dots & \dots & \dots \\ -1 & 1 & 0 & 0 & \dots & \dots & \dots \\ 0 & 0 & -1 & 1 & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \ddots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & l_{(m-1)m} & -u_{(m-1)m} \\ \dots & \dots & \dots & \dots & \dots & -1 & 1 \end{pmatrix}}_{\left(m \times \binom{m}{2}\right)}$$

and

$$Q = \underbrace{\begin{pmatrix} L_{12} & -U_{12} & L_{13} & -U_{13} & \dots & \dots & \dots \\ -1 & 1 & 0 & 0 & \dots & \dots & \dots \\ 0 & 0 & -1 & 1 & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \ddots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & L_{(s-1)s} & -U_{(s-1)s} \\ \dots & \dots & \dots & \dots & \dots & -1 & 1 \end{pmatrix}}_{\left(s \times \binom{s}{2}\right)}$$

in (SBMm-LPdual).
Having specified a suitable DEA-model for our investigation I now turn to describing the process of selecting relevant financial ratios.

3.2 Selecting relevant financial ratios

The task of selecting the "right" financial ratios for credit scoring is tricky as there is an abundance of candidates and a voluminous literature deals with what dimensions have to be considered.
In our case two aspects have a vital influence on the selection of the eventual ratios:

[7] In section 3.3 it will be shown how expert-opinions can be mapped into such upper and lower bounds.

1. Since a main component of our approach is the inclusion of expert opinions on the relative importance of the ratios that are eventually included, any initial choice of ratios will be relativized. In other words, the inclusion of expert opinions makes our results less sensitive to an initial choice that includes irrelevant or otherwise "wrong" ratios. Moreover, as the ultimate purpose of this paper is a practical answer to an empirical question, a theoretical discussion on the pros and cons of particular ratios would be beyond its scope.

   As a consequence, I want a choice of ratios that is as broadly and easily accepted as possible and able to stand the test in practice.

2. Even experts can make a reasonable judgment on the relative importance of only a limited number of ratios.

   As a consequence I want our choice of ratios to be as small as possible.

A workable solution to the above problem could be found with the help of the central bank of the Republic of Austria, the Oesterreichische Nationalbank (OeNB)[8]. The OeNB uses sophisticated sector-specific LOGIT-models to predict the probability of default one year ahead of a sample of 4000-5000 medium and large sized companies. Having data from 1981 onwards, these models achieve a very high AUROC[9] between 0.8 and 0.9, depending on the industry.
According to qualitative considerations, the OeNB first classifies all possible financial-ratio candidates (392) into the categories "liquidity", "profitability", "expense-structure", "management-quality", "financial analysis", "turnover" and "investment-analysis". After that, the number of financial-ratios is successively reduced based on a methodology well-established in the EURO-zone. It involves

1. univariate tests of discriminatory power,

2. tests on multicollinearity and

[8] I sincerely want to thank Dr. Gerhard Winkler of the OeNB for his help

[9] = the area below the ROC(="receiver operator characteristic")-curve: an indicator of the performance of the model. A value of 0.5 means that the model is no better than a random guess whereas 1 means a perfect forecast (cf. Blochlinger and Leippold, 2006)

3. an econometric derivation of the eventual selection of the financial ratios.

In our case, those financial-ratios were finally chosen that have the highest discriminatory power in the above categories as follows:

- Outputs (ratios to be maximized):
    1. Liquidity: $\frac{\text{operating cash flow}}{\text{current liabilities}}$
    2. Profitability: $\frac{\text{profit before tax}*100}{\text{balance sheet total}}$
    3. Expense-structure: $\frac{\text{profit before tax}*100}{\text{interest and similar expenses}}$
    4. Management-quality: $\frac{\text{profit before tax}}{\text{employees}}$
    5. Financial analysis: $\frac{\text{equity}*100}{\text{balance sheet total}}$
    6. Investment analysis: $\frac{\text{monetary current assets-current liabilities}}{\text{balance sheet total}}$
- Inputs (ratios to be minimized):
    1. Turnover: $\frac{\text{trade accounts payable}*360}{\text{turnover}}$

Having determined the relevant financial ratios, I can now turn to describing how the expert-opinions were gathered and mapped into the upper and lower limits as described in section 3.1.3.

3.3 Gathering expert opinions[10]

As discussed in section 3.1.3, the aim of asking experts for their opinions about the relative importance of the various financial ratios, was to determine upper and lower bounds of their relative weights in the solutions.

In order to be utilizable for our analysis, these judgments need to be available in a normalized way, i.e. I want to get something like table 1. For illustrative purposes let the weight for ratio r be u_r (r= 1, 2, 3, 4), in accordance with section 3.1.3. Therefore, $u_2 = 3.33$ of expert 1 means that he puts a weight of 33.3% on Ratio 2 when evaluating the credit-worthiness of a firm based on these 4 (fictitious) financial ratios. The ratio $u_2/u_1 = 3.33/1.67 = 2$ for expert 1, 3.16/2.11=1.5 for expert 2, 1.88/2.5=0.75 for expert 3, 2.00/2.00 for expert 4 and

[10] This section is largely taken from Cooper et al. (2000, p. 71 f.)

Expert	Ratio 1	Ratio 2	Ratio 3	Ratio 4	Sum
Expert 1	1.67	3.33	1.67	3.33	10
Expert 2	2.11	3.16	1.58	3.16	10
Expert 3	2.5	1.88	1.88	3.75	10
Expert 4	2	2	2	4	10
Expert 5	2.4	1.9	1.9	3.8	10
Average	2.14	2.45	1.81	3.61	10

Table 1: Fictitious table of normalized weights
Source: Cooper et al. (2000, p. 171)

1.9/2.4=0.79 for expert 5. Thus, I have the following range of the ratio u_2/u_1:

$$0.75 \leq u_2/u_1 \leq 2,$$

where 0.75 and 2 would be the L_{12} and the U_{12} of section 3.1.3. In the same way we can find the L_{ij} and U_{ij} for each pair (i, j) and thus all required data for the P- (Q-) matrix of section 3.1.3.

In principle, the experts could be asked about the relative importance of the various financial ratios directly (i.e. to fill in the numbers in the above table such that the sum of 10 results). The problem with that is, however, that it is difficult to consistently compare more than, say, 3 ratios like that. Saaty (1980)'s *analytic hierarchy process* (AHP) provides an elegant solution to this problem in that it creates a normalized weight-vector as in table 1 solely from each expert's pairwise comparison of the different financial-ratios. In other words, equipped with AHP, I can conveniently get all the data that I need to construct the P- and Q-matrices as discussed in section 3.1.3 for it allows the creation of simple questionnaires, in which a proband only needs to successively compare all possible pairs of financial-ratios.

I now have all the necessary ingredients to calculate efficiency scores, i.e. credit-default risks, with our DEA-model. I therefore now proceed to describing the last missing bit of our methodology, namely the comparison of the credit-default risk of entire industries based on such DEA-scores.

3.4 Comparing the efficiency of 2 industries

As already mentioned above, the main purpose of this paper is to check the hypothesis that the electricity-industry is characterized by a lower credit-default risk than the telecom-industry. This hypothesis implicitly presumes that the telecom- and the electricity-industry have different technologies, i.e. different efficient frontiers, so that efficiencies inferred from a pooled sample nor from distinct samples should be compared directly. If I found out, however, that electricity firms are, on average, closer to the efficiency frontier of the telecom-industry than vice versa, I'd still add strong evidence to the above hypothesis. I hence take the following approach:

Calculate the efficiency of each firm when evaluated with the technology of the other industry. Rank the thus obtained efficiencies of all firms in the sample and perform a so-called *rank-sum test* to check whether the ranking of electricity firms is statistically significantly better than that of the telecom firms.

In what follows therefore, I will first dwell on how my DEA-model needs to be adapted to manage such bilateral comparisons and then explain the functioning of the rank-sum test.

3.4.1 Adapting my DEA-model for bilateral comparisons

Based on (SBMm-LP)I formulate the following model:

$$\begin{aligned}
\min_{t,\Lambda,S^-,S^+,\Pi,\mathrm{T}} \quad & \theta = t - S^- \frac{1}{m} x_a I_m e_m \\
s.t. \quad & t + S^+ \frac{1}{s} y_a I_s e_s = 1 \\
& t x_a - [X_b, x_a]\,\Lambda - S^- + P\Pi = 0 \qquad \text{(SBMm-LP-bc)} \\
& t y_a - [Y_b, y_a]\,\Lambda + S^+ - Q\mathrm{T} = 0 \\
& t \geq 0,\ \Lambda \geq 0,\ S^- \geq 0,\ S^+ \geq 0, \\
& \Pi \leq 0 \text{ and } \mathrm{T} \geq 0
\end{aligned}$$

This way I make sure that each firm a of industry A is only compared with the technology of the other industry B and its efficiency ρ of

(SBMm) is still bounded by 0 and 1. Figure 1 is supposed to illustrate the concept with the input-minimization-part of the fictitious case of 2 inputs and one output[11]. The program determines the maximal slacks

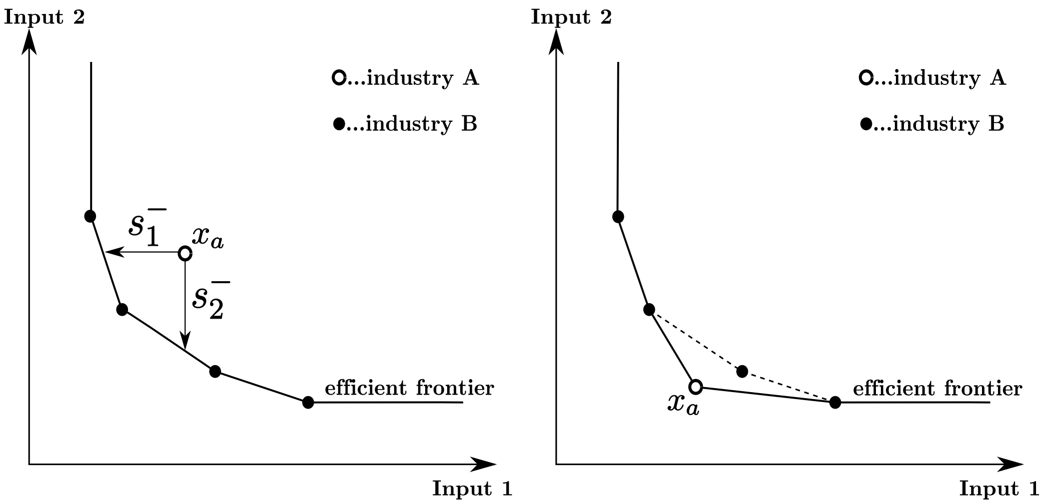

Figure 1: Bilateral comparison of industries

S_1^- and S_2^- of firm a and the according efficiency. In the left case the sum of the slacks is nonzero, therefore a would be inefficient, in the right case the sum of the slacks is zero, i.e. a would be part of the efficiency frontier of industry B and thus efficient.

3.4.2 The rank-sum test[12]

The rank-sum test, developed ba Wilcoxon-Mann-Whitney, is used to identify whether the differences between two groups are significant. In order to perform it, I take the sequence of ordered efficiencies C of all firms (i. e. in both industries), obtained as described in the previous section, and rank them in descending order to get the sequence R. If two or more firms exhibit identical efficiencies their rank is determined by the sum of their position in C divided by the amount of tied companies. So, for example, if $C = \{1, 1, 0.89, 0.67, 0.67, 0.56, \ldots\}$ the corresponding ranks are $R = \{1.5, 1.5, 3, 4.5, 4.5, 6, \ldots\}$. Following

[11]Remember: With the SBM-model the output-part plays an equally important role, the input-side is extracted solely for illustrative purposes.

[12]This section is largely taken from Cooper et al. (2000, p. 200 f.).

that, I calculate the rank-sum S of one of the two groups, in our case this would be the group of electricity enterprises. This statistic, S, is approximately normally distributed with mean $m(m+n+1)/2$ and variance $mn(m+n+1)/12$, where m is the number of enterprises of the chosen group and n is the number of enterprises in the other group. By normalizing S, I have

$$T = \frac{S - m(m+n+1)/2}{\sqrt{mn(m+n+1)/12}}, \tag{1}$$

where T has an approximately standard normal distribution. Using T, I can check the null hypothesis that the two groups have the same population at a level of significance α. Since I have a clear conjecture that the electricity enterprises are more efficient, such that a one-sided test suffices, I will reject this hypothesis if $T \leq -T_\alpha$, where $-T_\alpha$ corresponds to the lower percentile of the standard normal distribution[13]. This test, attributed to Wilcoxon, is essentially equivalent to the Mann-Whitney test.

Having specified our methodology, I can now proceed to the empirical part of the paper.

4 The Data

As indicated in section 3.3, to get the expert-opinions, questionnaires were compiled according to the principles of the AHP, such that a proband merely has to indicate as to how relevant he or she regards each of the 6 selected financial ratios[14] relative to every other selected output-ratio[15]. These questionnaires were sent out to the relevant people in the credit-departments of five major Austrian banks[16]. Using the AHP-technique, the replies were mapped into the following table of normalized weights.

[13] $-T_{0.05}$ would be -1.645.

[14] Only the output-ratios as listed in section 3.2 had to be compared, since I have only one input-ratio.

[15] So, in total, 15 questions had to be answered.

[16] I sincerely want to thank Friedrich Urbanek for helping me in this issue.

Expert	Ratio 1	Ratio 2	Ratio 3	Ratio 4	Ratio 5	Ratio 6
Expert 1	0.049	0.212	0.115	0.553	0.019	0.053
Expert 2	0.238	0.040	0.098	0.024	0.364	0.236
Expert 3	0.159	0.086	0.040	0.477	0.124	0.113
Expert 4	0.154	0.061	0.325	0.019	0.398	0.044
Expert 5	0.092	0.022	0.137	0.394	0.052	0.304

Table 2: Actual table of normalized weights

From this table the upper and lower bounds for the P- and Q-matrices were calculated as described in section 3.3.
The data for the financial ratios was collected from the 2006-annual reports of 22 “important” European electric utilities and 20 “important” European telecom-services providers. The selection of these samples was guided by two principles: comprehensiveness and randomness. The second principle is particularly important as the less theory-laden our selection, the bigger will be the explanatory power of our test of differences between the electricity- and the telecom industries. This “naive” approach led to samples of electric utilities and telecom-service providers that comprise the big pan-European players as well as more local smaller companies, diversified companies as well as companies that concentrate only on parts of the value chain.

5 The Results

The table below shows the main results of running (SBMm-LP-bc) with the above described data.

Rank	**Company**	**Industry**	**Efficiency**	**Ref. Set**
1.5	Belgacom	T	1	AXPO AG
1.5	TeliaSonera	T	1	AXPO AG
3	AXPO AG	E	0.50627344	Belgacom, TeliaSonera
4	Verbund	E	0.11938396	TeliaSonera
5	CEZ AS	E	0.11206751	TeliaSonera
6	Vodafone	T	0.0147119	AXPO AG
7	Scottish Power	E	0.01128987	TeliaSonera

Rank	**Company**	**Industry**	**Efficiency**	**Ref. Set**
8	Vattenfall Europe AG	E	0.00737199	Belgacom, TeliaSonera
9	ATEL AG	E	0.00593683	TeliaSonera
10	Swisscom	T	0.00579277	AXPO AG
11	Telenor	T	0.00565085	AXPO AG
12	Red Electrica De Espana	E	0.00543322	TeliaSonera
13	KPN	T	0.00398886	AXPO AG
14	Hafslund ASA	E	0.00331133	Belgacom, TeliaSonera
15	EON AG	E	0.00297812	TeliaSonera
16	National Grid	E	0.00284788	TeliaSonera
17	Scottish&Southern	E	0.00280892	TeliaSonera
18	Vivendi Universal	T	0.00243782	AXPO AG
19	ELIA	E	0.00222797	Belgacom, TeliaSonera
20	Endesa	E	0.0021712	TeliaSonera
21	Electrabel SA	E	0.00214957	TeliaSonera
22	ENEL	E	0.00210892	Belgacom, TeliaSonera
23	Iberdrola SA	E	0.00204826	TeliaSonera
24	OTE	T	0.00204823	AXPO AG
25	Telekom Austria	T	0.00158994	AXPO AG
26	Electricite de France	E	0.00147221	Belgacom
27	Matav	T	0.00133386	AXPO AG
28	EVN	E	0.00132867	Belgacom, TeliaSonera
29	EnBW	E	0.00120607	TeliaSonera
30	Portugal Telecom	T	0.00112667	AXPO AG
31	TDC	T	0.00100437	AXPO AG
32	Telecom Italia	T	0.00099642	AXPO AG
33	RWE	E	0.00090183	Belgacom
34	Suez SA	E	0.00068688	Belgacom, TeliaSonera
35	Telefonica	T	0.00060592	AXPO AG
36	BT	T	0.00051291	AXPO AG
37	TPSA (Poland)	T	0.00050398	AXPO AG
38	France Telecom-Orange	T	0.00036136	AXPO AG
39	Deutsche Telekom	T	0.00029404	AXPO AG
40	Cable&Wireless	T	0.00018686	AXPO AG
41	Svyazinvest 2005	T	0.0001369	AXPO AG

Rank	**Company**	**Industry**	**Efficiency**	**Ref. Set**
42	Public Power Corp (Greece)	E	9.87E-05	TeliaSonera

Table 3: Ranking of efficiencies

Where the first column is equivalent with R from section 3.4.2, the third column shows to what industry the respective enterprise belongs to, the fourth column shows the efficiency of the respective enterprise (i. e. its relative credit-worthiness) and the fifth column shows its reference set, i. e. the enterprises that are its closest neighbors on the efficiency frontier.

From table 3 I calculate the S-statistic of the electricity industry: 407. Plugging this, together with $m = 22$ (the number of electricity companies) and $n = 20$ (the number of telecom companies) into (1) yields

$$T = -1.662.$$

According to the Wilcoxon-Mann-Whitney-Test, described in section 3.4.2, I can therefore reject the null hypothesis that the telecom and the electricity industries have the same population at $\alpha = 0.05$, as $T \leq -1.644$, the relevant critical value. In other words, the electricity industry on the whole indeed has a significantly lower credit-default risk than the telecom industry.

6 Conclusion

The purpose of this paper was to add evidence to the controversial question whether there is a significant difference in the credit default risk of the electricity and the telecom industry. Realizing that the conventional methods to measure the credit default risk of enterprises based on financial ratios can hardly be employed to answer this particular question and that, on the other hand, its basic conception makes it well applicable to this field, a DEA-based method was developed by which the credit default risk of industries can be compared.
This method consists of the following 2 main steps:
First, the relative credit-worthiness of each firm is assessed with a slack-based measure of efficiency (SBM) DEA-model where financial ratios that should be as small as possible play the role of inputs and financial ratios that should be as big as possible play the role of outputs. My SBM-model differs from the original one in that it is able to incorporate expert-opinions on the permissible relative sizes of the various in- and outputs. Moreover, in order to make the efficiency scores of the enterprises of the two different industries comparable, each company is evaluated with respect to the technology of the other industry.
Second, the thus obtained efficiencies of all enterprises are ranked and a rank-sum test is performed to test the hypothesis that the two groups belong to the same population.
The application of this method to the data of 22 representative European electric utilities and 20 representative European telecom service providers led to a clear rejection of this hypothesis so that I can firmly state that the electricity industry is, on average, characterized by a lower credit default risk than the telecom industry.

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