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On the Efficiency of Steel Sectors in EU Member Countries

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Abstract

Steel is one of the most multifunctional and most adaptable materials, and the iron and steel sector is a strategically important part of European industry. Steel products are vital for other industries including the construction to automotive sectors. Currently, the steel-producing companies in the EU face strong competition from non-EU (mainly Asian) countries, which exerts pressure on their efficiency. In this paper, we explore the efficiency of the steel sectors of EU members using the PROMETHEE method, which provides a clear graphical representation of the results. The aim is to compare the efficiency of the EU steel industries. We identify the input and output factors whose values differ by countries (e.g. price of input materials imported from outside the EU or the final product sale prices significantly influence the steel sectors, but their values are more or less identical for all EU countries). In our study, we involved three inputs (labour costs in the sector, number of employees and energy consumption) and three outputs (value of production, costs of emissions trading and net export). The results show that only 3 of 19 explored sectors are technically efficient (Bulgaria, Slovakia and Belgium). In line with Ishizaka et al. (2018), all the sectors are also classified into four groups: efficient, effective, inefficient and frugal.

Keywords

Efficiency, environment, outranking, PROMETHEE, steel industry.

JEL Classification: C61, L61

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1. Introduction

Efficiency is a desirable state for each economic subject guaranteeing that no more outputs can be obtained with the same number of inputs (or vice versa). The process of transformation of inputs to outputs is apparent in manufacturing companies, so production is a frequent object of efficiency evaluation.

In this paper, we explore the European iron and steel industry and its behaviour. We evaluate the technical efficiency of the steel sectors of EU countries. We chose the steel sector for several reasons. First, steel is a strategically important material found everywhere around, including in means of transport (cars, aircrafts), building construction (transoms, beams, reinforced concrete) or various household equipment (boilers, pots). Second, the EU steel industry is one of the industrial sectors most threatened by non-European (mainly Asian) competitors. Importers into the EU usually benefit from low labour costs, less strict environmental policy or returns to scale. Last but not least, there is a research gap in this field – all of the studies published so far have been too simplified in some way, as will be discussed in the current state-of-the-art analysis below.

In this paper, we focus on the level of the national steel sectors – that is, we do not work with individual companies (although some smaller sectors consist of only a couple of companies) and we do not work with any entity outside the EU. We will therefore be able to identify the weaknesses of the sectors that should be reduced or at least eliminated to achieve efficiency within the EU steel industry.

Efficiency measuring in industry has been a frequent object of mathematical modelling. Nazarko and Chodakowska (2017) investigated the EU construction industry; Kočišová (2015) dealt with European agriculture; Sueyoshi and Wang (2018) focused on the U.S. petroleum industry; Chou et al. (2012) explored the Chinese IT sector; and Wang et al. (2014) compared efficiency of all the U.S. industrial sectors. The steel industry has not been ignored. Some studies analysed only a single national steel sector – such as Poland (Baran et al., 2016), Sweden (Morfeldt and Silveira, 2014), China (Wei et al., 2007; Chou et al., 2012), Russia (Parshin, 2015) or the USA (Wang et al., 2014). Some studies analysed only a single steel company and its behaviour (van Caneghem et al., 2010). It is possible to build on these studies when analysing the national steel sectors in the EU, but the involved factors must be reconsidered in terms of relevance and availability. These studies also often simplified the production process and followed only selected parts, such as energy efficiency (Wei et al., 2007; Moya and Pardo, 2013; He et al., 2013) or environmental efficiency (van Caneghem et al., 2010; Wang et al., 2014). In the case of the steel industry, economic and environmental factors are both highly important – according to Karali, Xu and Sathaye (2014), more than 5% of all CO_2 emissions are released within the iron and steel sector – so we include both in our analysis. Moreover, these two groups of factors are related due to emissions trading within the European Emissions Trading System (EU ETS), which we also incorporate into our study. Further details on the structure of our model can be found in section 3.

Efficiency evaluation can be done using several quantitative methods. By far the most popular approaches to efficiency evaluation are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Both have been used to evaluate the efficiency of industrial sectors (Wei et al., 2007; Chou et al., 2012; Morfeldt and Silveira, 2014; Kočišová, 2015; Baran et al., 2016). However, we have decided to use another method in this paper – the PROMETHEE method. In line with Ishizaka, Resce and Mareschal (2018), this popular method of multi-attribute decision-making can be used also to evaluate the technical efficiency of production units. It provides two main advantages over the methods mentioned above. First, it is easy to analyse where and how the final evaluations are generated. Second, regardless of the size of the problem, the results can always be presented graphically. Last but not least, the PROMETHEE-based approach can be used without any further modification to handle negative data and for both minimizing and maximizing factors (there is no need to distinguish between desirable and undesirable factors).

The proposed model is run with real data on 18 EU national sectors for the year 2017, for which all values are available.

The rest of this paper is organised as follows. In section 2, we provide the methodology for the PROMETHEE method. Section 3 is devoted to the structure of the model (inputs and outputs are identified and explained) and the related input data. The core section of this paper is Section 4, where the efficiency of the steel sectors is evaluated, graphically presented and discussed. The paper is concluded in Section 5.

2. PROMETHEE for efficiency evaluation

The PROMETHEE method was developed by Brans et al. (1986) to present an easily understandable and user-friendly method for ranking alternatives. That they were successful is proved by Behzadian et al. (2010) and their review of the published applications of the PROMETHEE method. The original algorithm serves to find the rankings of (discrete) alternatives with respect to a given set of criteria. Many extensions of the original algorithm have been introduced over the last two decades, and one of these extensions is used in this paper. We use the PROMETHEE-based algorithm introduced by Ishizaka, Resce and Mareschal (2018), which focuses on efficiency evaluation. This section provides a brief description of the original algorithm for ranking of alternatives, which is necessary for further analysis, and also the extension for efficiency evaluation. The PROMETHEE method algorithm for the complete ranking of alternatives can be summarised into the following steps:

1. Preference degrees $P_i(A_x, A_y) \in [0,1]$ are calculated for all pairs of alternatives A with respect to each criterion $i = 1, \ldots, k$ using the preference function P_i (this function assigns a preference degree to each possible difference in performance values). The preference degree says how much the decision maker prefers an alternative with better performance in the given criterion to the one with worse performance.

2. The preference degrees are aggregated to preference indices π. This is done using the sum product of preference degrees and weights:

$$\pi(A_x, A_y) = \sum_{i=1}^{k} w_i \cdot P_i(A_x, A_y). \tag{1}$$

$$\pi(A_x, A_y) = \sum_{i=1}^{k} w_i \cdot P_i(A_x, A_y).$$

The preference index $\pi(A_x, A_y)$ expresses how strongly A_x is preferred to A_y with respect to all the considered criteria. The weights w_i must be normalised, that is, $\sum w_i = 1$. Note that $\pi(A_x, A_y)$ is again in $[0,1]$ for all variations of the alternatives.

3. The preference indices are aggregated to the positive and negative flows ($\phi^+ \in [0,1], \phi^- \in [0,1]$) of each alternative, see (2) and (3). The positive flow of an alternative is a mean value of the preference indices comparing this alternative with the others (how much better the alternative is compared to the other

$$\phi^+(A_x) = \frac{\sum_{j=1, j\neq x}^{s} \pi(A_x, A_j)}{s-1}, \tag{2}$$

alternatives):

where s stands for the number of alternatives. The other way around, the negative flow of an alternative is a mean value of the preference indices comparing the remaining alternatives with the one under evaluation (how much worse the alternative is than the other alternatives):

$$\phi^-(A_x) = \frac{\sum_{j=1, j\neq x}^{s} \pi(A_j, A_x)}{s-1}. \tag{3}$$

The positive flow of an alternative shows how strongly we prefer this alternative to the remaining ones (again with respect to all criteria); meanwhile, the negative flow of an alternative expresses how strongly we prefer the remaining alternatives to the given alternatives.

4. Because ranking using only positive and negative flows provides only a partial ranking (see Brans et al. 1986), these partial flows must be aggregated to net flows $\phi \in [-1,1]$:

$$\phi(A_x) = \phi^+(A_x) - \phi^-(A_x). \tag{4}$$

It can be seen that the results of all the steps of the PROMETHEE algorithm depend on the preference function. The problem is that there is not one unique preference function that can be used to calculate preference degrees. Brans et al. (1986) introduced six types of preference functions from which the decision maker should choose. The Gaussian preference function is one of these six types (shapes), see Figure 1 ($\boldsymbol{\sigma_i}$ stands for standard deviation of the performances in the $\boldsymbol{i}$-th criterion of all alternatives; $\boldsymbol{d_i}$ is the difference in performances of two alternatives) and (5).

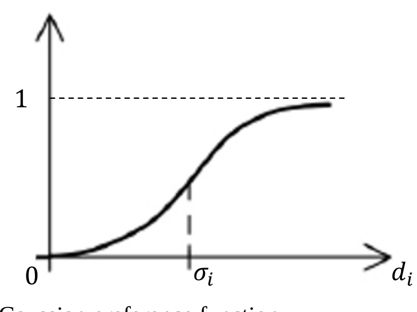

Figure 1 Gaussian preference function

$$P_i(d_i) = 1 - \exp\left(\frac{-d_i^2}{2\sigma_i^2}\right) \quad (5)$$

The net flows of alternatives are very important for evaluating their efficiency because they are used as input data for the algorithm from Ishizaka et al. (2018). The authors of this algorithm proposed splitting the set of criteria into two subsets – input and output criteria. The original PROMETHEE algorithm described above is then run twice, once for each subset of criteria separately. The result is a 2-element description of each alternative – each alternative is given two values of net flows (net flow for inputs ϕ_I and net flow for ouputs ϕ_O). At the end, the results are presented in the $(\phi_\mathrm{I}, \phi_\mathrm{O})$-plane, an example of which is shown in Figure 2. To keep the usual logic of the graphical representation known from, for example, the Markowitz *mean-risk* plane, the values of ϕ_I are transformed to their opposite values by multiplying by -1 (thus the most preferred position is a top-left corner).

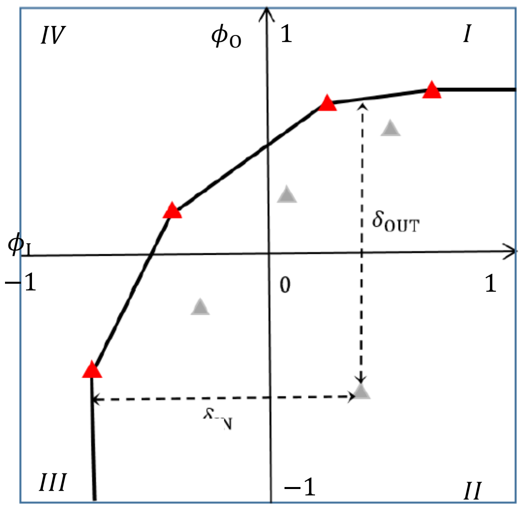

Figure 2 Gaussian preference function

In Figure 2, the efficiency of eight alternatives is explored. Four of them are considered technically efficient (red triangles) and the remaining four alternatives inefficient (grey triangles). If necessary, it is also possible to measure the distance of inefficient alternatives to the PROMETHEE productivity analysis (PPA) frontier to determine how much their performance must be improved to become efficient (a two-step algorithm based on the standard additive DEA model for this measurement has been suggested by Ishizaka, Resce and Mareschal, 2018), see the dashed lines in Figure 3.

Besides the PPA frontier in Figure 2, Ishizaka, Resce and Mareschal (2018) also proposed interpreting the results using the quadrants of the $(\phi_\mathrm{I}, \phi_\mathrm{O})$-plane:

- **Quadrant *I* – Effective alternatives**: Alternatives focused on high production. From the microeconomic point of view, very large companies are usually included in this group.
- **Quadrant *II* – Inefficient alternatives**: These alternatives produce a low output with a high input. They are uneconomical and should be improved if they want to survive in the long-term.
- **Quadrant *III* – Frugal alternatives**: Alternatives that minimise spending money.
- **Quadrant *IV* – Efficient alternatives**: These alternatives produce a high output with a low input. This performance is naturally the most preferable.

3. Input and output criteria for the model

To get relevant and reliable results for the efficiency evaluation, it is necessary to choose the sets of inputs and outputs carefully. In this study, we built on the analysis provided in the available studies and the expertise of an expert in the steel industry. The following factors were identified as extremely important for steel companies (I = input, O = output, EC = economic factor, ENV = environmental factor):

- price of fuel$^{\mathrm{I,EC}}$ (coal, coke, oil, gas), see Sueyoshi and Wang (2018),
- consumption of fuel$^{\mathrm{I,EC/ENV}}$ (coal, coke, oil, gas), see Wei et al. (2007) or Morfeldt and Silveira (2014),
- consumption of energy$^{\mathrm{I,EC/ENV}}$ (He et al., 2013; Morfeldt and Silveira, 2014),
- labour price and number of employees$^{\mathrm{I,EC}}$ (Baran et al., 2016),
- production of steel, various steel products and semi-products$^{\mathrm{O,EC}}$ (Baran et al., 2016; Wei et al., 2007),
- value of production$^{\mathrm{O,EC}}$ (Baran et al., 2016; He et al., 2013),
- emissions$^{\mathrm{O,ENV}}$ (Zapletal et al., 2019; Sueyoshi and Wang, 2018, He et al., 2013),
- free carbon allowances$^{\mathrm{I,ENV/EC}}$ (Zapletal et al., 2019),
- price of carbon allowances$^{\mathrm{,ENV/EC}}$ (Zapletal et al., 2019),
- balance of carbon allowances$^{\mathrm{O,ENV/EC}}$ (Zapletal et al., 2019),
- net export$^{\mathrm{O,EC}}$ (Quirion, 2003).

Although all of the above factors can influence the performance of steel production, some cannot be considered in this study because their values are (more or less) the same for all sectors, including fuel prices, production prices and the price of emission allowances. The environmental factors related to emissions trading within the EU ETS are aggregated into the costs of emissions trading ($CoET$) because these costs are in fact the main consequence of the impact of the EU ETS. $CoET$ is calculated as *CO_2 emissions* minus *free allowances*, and the result is multiplied by the *price of allowances*. It is obvious that $CoET$ is an undesirable output.

We also decided not to involve the production quantity. Many different types of steel products exist, and it is a substantial difference if a sector produces 1 tonne of crude steel or 1 tonne of seamless tubes in terms of the value added. Therefore, we represent the final production only by the value of production, which does not consider production homogenous.

In conclusion, we work with three inputs:

- *I1*: number of employees (min),
- *I2*: hourly labour costs [EUR] (min),
- *I3*: energy consumption [GWh] (min),

and three outputs:

- *O1*: value of production [M EUR] (max),
- *O2*: value of net export [M EUR] (max),
- *O3*: costs of emissions trading [K EUR] (min),

where min/max indicates if a factor is minimised or maximised (note that the last output is undesirable).

The input data for the selected factors were derived from several databases. The values for *I2* and *I3* were taken from the Eurostat database[1] (this database also provides data on *O1*, but they are incomplete). More specifically, we worked only with data on the *Manufacture of basic metals* according to the NACE classification (Division no. 24). The data on *I1*, production volumes (necessary for *O1*) and net export volumes (necessary for *O2*) were taken from Eurofer (2018). *O1* and *O2* require knowledge of average steel product prices, which are available in the MEPS database[2] (we distinguish crude steel, flat products, long products and tubes). To calculate the values for *O3*, we had to find input data for the quantity of CO_2 emissions and free allowances (CarbonMarketData database[3]) and the prices for carbon allowances (SendeCO2 trading platform[4]).

All input data are considered for 2017 (yearly data such as *I1*, *I2*, *O2*), 17 December (monthly data such as product prices) and 29 December 2017 (daily data carbon price only).

4. Results of the analysis

Before running the model, we set some remaining required parameters for PROMETHEE, including types of preference functions and the weights of alternatives.

We used the Gaussian preference function type (see Figure 1) for each criterion with σ_i equal to the standard deviation of performance for all sectors in the i-th criterion. This setting has already been used by Shi et al. (2007) and Husinec at al. (2019), and it is suitable for quantitative criteria where a decision maker is not able (or does not want) to set either an indifference threshold (the maximum value for which a difference in the performance of two alternatives is ignored in terms of preference) or a preference threshold (the minimum value of differences that is preferred absolutely).

The last parameters were the criteria weights. We used the same weights for all six criteria used (three inputs and three outputs) because it would be very problematic to distinguish their importance. Although the considered criteria can be measured in money (*number of employees* and *hourly labour costs* could be easily aggregated to *cost of employees*), which would make the values comparable, this approach would not be correct for our analysis because making money is definitely not the only one goal of the industrial sectors. For example, net exports are important for countries in terms of their self-sufficiency in the analysed field. The cost of emissions trading also involves environmental performance – they reflect the carbon burden (the more CO_2, the higher the cost of emissions trading). Thus, if the costs of emissions trading reaches only 1% (or 2%) of the value of production, it does not mean that they are 100 (or 50) times less important.

The model was run using Visual Promethee software. All the input data can be found in Appendix 1.

The results of the efficiency analysis can be found in Figure 6 (see in Appendix). Only three countries are considered technically efficient (on the PPA frontier) – Bulgaria, Slovakia and Belgium. The Bulgarian steel sector is very small and its success stems from good performance in inputs (especially low labour costs). The Slovakian steel sector has a long tradition and belongs among the *middle-sized* sectors considering the production volume. Like Bulgaria, its biggest advantage lies in low labour costs and the performance

[1] Available on https://ec.europa.eu/eurostat/data/
[2] Available on http://www.meps.co.uk/flat&longcarbonprice1.htm
[3] Available on https://carbonmarketdata.com/en/home
[4] Available on https://www.sendeco2.com/it/prezzi-co2

in the remaining criteria are more or less average (it does not have any major weaknesses). A completely different profile can be seen for Belgium. The Belgian steel sector is quite large and well established. It performs the best in terms of net exports, the second best in emissions costs and it has only one significant drawback – very high labour costs.

The performance of all three efficient sectors is also shown in Fig. 3 – Fig. 5. The radius of the largest circle equals 2 and the values correspond to the net flows ϕ. If the performance is closer to the outer circle than to the centre, the ϕ value generated by the given criterion is positive and this criterion is a strength of the alternative (and vice versa). The layout of the axes is also worth noting; it is the result of the so-called GAIA analysis, based again on the PROMETHEE rankings (for more information, see Mareschal and de Smet, 2009). The more similar the direction of the two axes, the more similar the performances in terms of their contribution to the net flow values ϕ. You can see that *energy consumption* is positively dependent on the *number of employees* and negatively dependent on the *value of production* and *costs of emissions trading*, which is natural because all of these factors depend on the production volume. Perhaps more interesting is the strong negative dependence between *net export* and *labour costs*, signalling that sectors with better balance of trade are expected to have higher labour costs. This result can be explained in the following way. The sectors with high labour costs (like Belgium) are more likely focused on manufacturing products with higher added value and, vice versa, importing rather basic and low-cost and semi-finished products.

As to the efficiency evaluation according to Ishizaka et al. (2018) presented in Section 2, clusters of sectors with similar performances can be identified:

1. Large sectors with high production values and weak performance in input criteria (Belgium, Italy, Germany, France and Spain).
2. Small frugal sectors with low production values (Bulgaria, Hungary, Greece and Slovenia).
3. Middle-sized sectors with a long tradition of GDP below the EU average. These sectors perform quite badly in terms of *net export* (the imported value is higher than the exported one), but take advantage of low labour costs. In terms of the remaining criteria, they perform more or less on average. Using the terminology of Ishizaka et al. (2018), these sectors are somewhere between being *frugal* and *efficient* (Slovakia, the Czech Republic, Romania and Poland).
4. Steel sectors in economically strong countries. Their performance in output is similar to the previous group, but high labour costs put them at a disadvantage. In comparison with the previous group, these countries perform better in terms of *net export*, but surprisingly a little bit worse in *costs of emissions* in general. These sectors cannot be unambiguously classified to any of the four groups of efficiency established by Ishizaka et al. (2018; United Kingdom, the Netherlands, Finland and Sweden).

Besides the results described above, it is also reasonable to explore the robustness of these results. Sensitivity analysis within the PROMETHEE-based methods is usually done for changing weights (Albadvi et al., 2007). In this paper, we used equal weights for all of the involved factors because there is no natural reason to distinguish between them. To explore how stable the results are, we ran the model again with the weights of each factor increased and decreased by 5 percentage points (p.p.; e.g. the weight of labour costs decreased/increased by 5p.p., meanwhile the weights of the two remaining inputs increased/decreased by 2.5p.p.). The results of the sensitivity showed that the set of efficient countries/sectors remains the same for all considered changes, except for one – the Italian steel sector becomes efficient when the weight of net exports decreases by 5p.p. The original results are therefore quite robust.

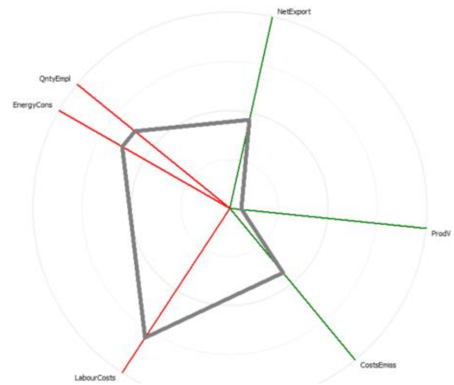

Figure 3 Detailed performance of the Bulgarian steel sector

Figure 4 Detailed performance of the Slovakian steel sector

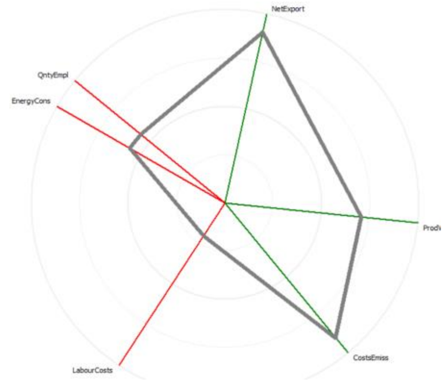

Figure 5 Detailed performance of the Belgian steel sector

5. Conclusion

The European steel industry is a strategic industrial sector providing inputs for most other sectors of industry. It is threatened by competition coming from outside the EU and by EU environmental policies (emissions trading). An effort to measure and improve the efficiency of the EU state steel sectors is natural. This study assessed the efficiency of these sectors from both the economic and environmental perspectives.

Using the PROMETHEE-based method for efficiency evaluation, we assessed 18 sectors and their performance. Only three sectors were considered technically efficient (Bulgaria, Slovakia and Belgium). Four groups of steel sectors were also identified according to their efficiency: 1) large sectors focused on quantity of products; 2) small frugal sectors with good performance in inputs but low outputs; 3) middle-sized sectors with low labour costs, bad net export but average other performances; and 4) sectors in economically strong countries with high labour costs and output performance similar to those in group 3.

The contribution and limitations of this paper are closely related. To the best knowledge of the authors, this study is a pioneer in the efficiency evaluation of EU steel industries involving economic and environmental factors. However, this also means that the results cannot be compared with prior results. Future research should be devoted to dynamic analysis to explore the development of performance over time. Clarifying the uncertainty in input data (e.g. price of emission allowances) is also warranted.

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Appendix

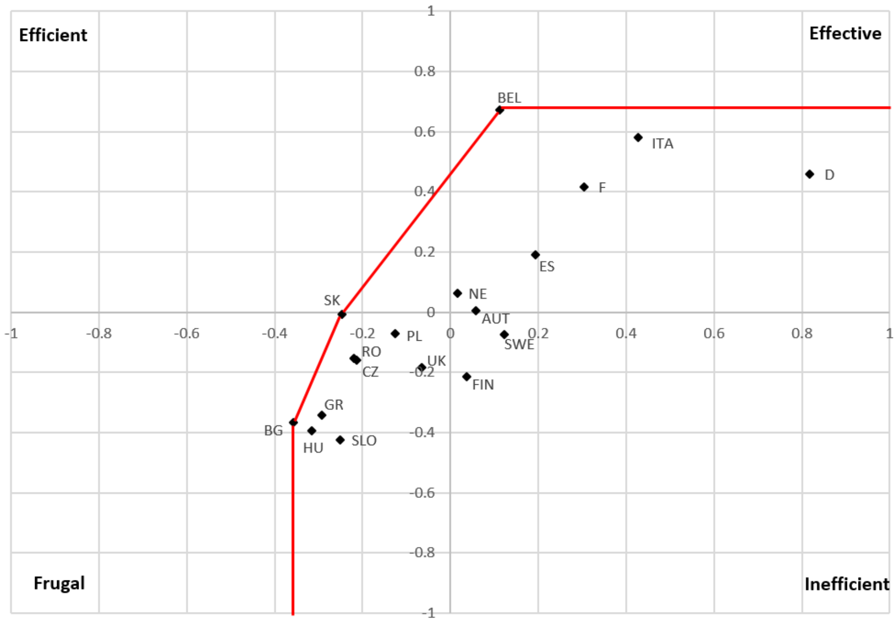

Figure 6 Efficient frontier and performance of the EU steel sectors