Abstract

Small Medium-sized Enterprises (SMEs) face many obstacles when they try to access credit market. These obstacles are increased if the SMEs are innovative. In this case, financial data are insufficient or even not reliable. Thus, when building a judgemental rating model, mainly based on qualitative criteria (soft information), it is very important to finance SMEs’ activities. Until now, there isn’t a multicriteria credit risk model based on soft information for innovative SMEs. In this paper, we try to fill this gap by presenting a multicriteria credit risk model, specifically, ELECTRE-TRI. To obtain robust SMEs’ assignments to the risk classes, a SMAA-TRI analysis is also implemented. In fact, SMAA-TRI incorporates ELECTRE-TRI by considering different sets of preference parameters and uncertainty in the data via Monte Carlo simulations.

Finally, we carry out a real case study, with the aim of illustrating the multicriteria credit risk model proposed.

Keywords: Multiple Criteria Decision Aiding; qualitative criteria; SMAA-TRI; innovative SMEs; judgmental credit rating model.

1 Introduction

Since small and medium-sized enterprises (SMEs) are the backbone of all economies, scholarly attention to their credit risk assessment has considerably increased.

SMEs face many financial restrictions to access the credit market (for example see Berger et al., 2005, Beck and Demirgüç-Kunt, 2006 and Canales and Nanda, 2012). Moreover, if the SMEs are newly created firms innovative, these restrictions are more tight (see Brown et al., 2009).

Consequently, there exists a finance gap within the SME’s sector, and such a condition is worsened when SMEs have to request credit to the banks. Banks usually adopt different lending approaches that can be grouped in four categories: financial statement lending (based on the evaluation of information from balance-sheet data), asset-based lending (based on the provision of a collateral), credit scoring models (based on hard information), and relationship lending (see Moro and Fink, 2013).

More precisely, the credit scoring models are grouped in the families: statistical, operational research and intelligent techniques (see Kumar and Ravi, 2007 and Crook et al., 2007 for a review on the topic). In financing SMEs, there is a recent research debate on which is the best type of lending technique.

From one hand, there are several papers supporting the idea that banks prefer to finance SMEs on the basis of a long and strong activity of relationship banking, a type of lending mainly based on non-financial information (soft information) (see among others Moro and Fink, 2013 and Berger and Udell, 1996).

On the other, there is a recent stream of research that asserts that big banks lend more easily to SMEs if lending techniques based on hard information are adopted (see for example Berger and Udell, 2006 and Beck et al., 2011).
Owing to the SMEs’ lack of sufficient or reliable track records, a qualitative rating based on the judgment of some experts (judgemental rating) seems the most useful approach to evaluate the SME’s creditworthiness.

In fact, the significant role of the non-financial criteria for the SME’s credit risk evaluation is supported by several research papers (see among others Altman et al., 2010, Auken et al., 2010, Berger et al., 2005 and Grunert et al., 2005; and specifically, for innovative SMEs see for example Shefer and Frenkel, 2005 and Czarnitzki and Hottenrott, 2011).

Until now, to the best of our knowledge, there isn’t a judgemental credit scoring model for innovative SMEs. In this paper, we try to fill this gap by adopting a Multiple Criteria Decision Aid (MCDA) approach (Vincke, 1992). Since the financing of innovative SMEs is an uncertain problem due to several and conflicting aspects, the Multiple Criteria Decision Aid approach (also called the constructive approach Roy, 1993) seems the most useful (see Greco et al., 2013 for some useful comments on this topic).

Several multicriteria approaches have already been adopted to predict business failures, that is a typical sorting problem (see Zopounidis and Doumpos, 2002). Most of them rely on a utility function to classify enterprises into two categories: the default and non-defaulted (see among these the multicriteria hierarchical discrimination approach proposed in Doumpos et al., 2002). Even some multicriteria approaches relying on a utility function have been proposed with the aim of helping credit granting decisions; for example the multicriteria methodology MACBETH (introduced in Bana e Costa and Vansnick, 1997 and Bana e Costa and Vansnick, 1999) has been implemented as a qualitative credit rating model in the banking sector (see Bana e Costa et al., 2002).

Very few recent papers have also developed some credit rating models based on an outranking relation; for example, ELECTRE TRI (firstly, introduced in Yu, 1992) has been implemented for the first time as a quantitative credit rating model in Zopounidis and Doumpos, 2011 and PROMETHEE II (Brans and Vincke, 1985) applied for banks’ rating evaluation (Doumpos and Zopounidis, 2010). Moreover, a first attempt to estimate SMEs’ performance, based on a financial ratio analysis, can be found in Voulgaris et al., 2000, where the multicriteria sorting approach, UTADIS (Jacquet-Lagrézé, 1995) has been applied. Recently, in Nemery et al., 2012 the innovation performances of SMEs have been assessed by the Flow-Sorting method. However, none of these papers attempts to develop a judgemental rating model to assign innovative SMEs into risk classes. The aim of the paper is to fill this gap by presenting a multicriteria model to assist financial institutions in the evaluation of the risk involved in financing innovative projects.

First, we propose ELECTRE TRI to evaluate the SMEs’ credit risk, mainly on the basis of qualitative criteria. To obtain robust SMEs’ assignments to the risk classes, a SMAA-TRI analysis (Tervonen et al., 2007) has also been implemented. In fact, SMAA-TRI incorporates ELECTRE-TRI by considering different sets of preference parameters and uncertainty in the data with Monte Carlo simulations.

Then, to illustrate the multicriteria methodology proposed a real case study on four Italian innovative enterprises in the phase of start-up is considered. The whole multicriteria approach has been implemented by interviewing some loan officers from one of the main Italian banks.

Moreover, preliminary to the multicriteria analysis, we have evaluated the financial soundness of the start-up considered outperforming a scenario analysis on the basis of their Business Plans. The financial analysis has been conducted along two directions. On one hand, a NPV for each scenario has been computed. On the other, financial ratios have been evaluated and included in the multicriteria analysis.

The paper is organized as follows. In Section 2, we provide a brief description of ELECTRE-TRI and SMAA-TRI. In Section 3, we describe the main phases of the multicriteria rating model proposed to evaluate the riskiness of innovative SMEs. A real case study is carried out in Section 4 to illustrate the judgemental multicriteria credit risk rating presented. Section 5 gives some useful
managerial insights on the results obtained by the methodology considered. Finally, some conclusions are included in Section 6.

2 A sorting model

In this paper, the multicriteria approach ELECTRE-TRI (Yu, 1992) has been proposed as a credit rating model to assign innovative SMEs into risky categories. ELECTRE-TRI has been implemented in the framework of SMAA-TRI, to take into account uncertainty and imprecision in its preference parameters. In the next sections, we provide a brief description of ELECTRE-TRI and SMAA-TRI.

2.1 An overview of ELECTRE-TRI method

Let $A = \{a_1, a_2, \ldots, a_i, \ldots, a_m\}$ be a finite set of $m$ alternatives to be assigned on the basis of a consistent family of $n$ criteria $G = \{1, 2, \ldots, n\}$ to $p$ risk ordered categories $C_p \succ \cdots C_k \cdots \succ C_1$, where $C_{k+1}$ consists of a group of alternatives, better than those in $C_k$. An alternative $a_i \in A$ evaluated on the set of $n$ criteria is denoted by:

$$a_i = (a_{i1}, \ldots, a_{ij}, \ldots, a_{in}),$$

where $a_{ij}$ indicates the evaluation of the alternative $a_i$ on criterion $j$.

Every group of alternatives is separated from the others by means of risk profiles: $b_{p-1}, \ldots, b_k, \ldots, b_1$. Each profile $b_k$ is the upper limit of the group $k$ and the lower limit of group $k + 1$. For example, considering two ordered classes, $C_2$ could represent the financed enterprises, while $C_1$ groups the ones non-funded. As a result, one risk profile $b_1$ delimits two risk categories to which an enterprise has to be assigned. The alternatives are assigned to the risk classes on the basis of their comparisons with the risk profiles exploiting the two outranking relations $a_iSb_k$ and $b_kSa_i$, which mean, respectively, that alternative $a_i$ is at least as good as the profile $b_k$ and vice versa.

The exploitation of each outranking relation consists of two phases: the concordance and discordance test. Roughly speaking, the concordance test indicates the level of majority of criteria that supports the outranking relation $a_iSb_k$ (or $b_kSa_i$), while the discordance test represents the strength of the minority of criteria that oppose a veto to the outranking relation $a_iSb_k$ (or $b_kSa_i$).

The concordance test is performed by the computation of the concordance index $C(a_i, b_k)$:

$$C(a_i, b_k) = \sum_{j=1}^{n} w_jc_j(a_{ij}, b_k),$$

where $w_j$ indicates the weight of criterion $j$ with the weights summing up to 1 and $c_j(a_{ij}, b_k)$ is the partial concordance index with respect to criterion $j$ of the assertion “$a_i$ is at least as good as the profile $b_k$.” The partial concordance index $c_j(a_{ij}, b_k)$ is computed as follows:

$$c_j(a_{ij}, b_k) = \begin{cases} 0 & \text{if } a_{ij} \leq b_{kj} - p_j \\ \frac{a_{ij} - b_{kj} + p_j}{p_j - q_j} & \text{if } b_{kj} - p_j < a_{ij} < b_{kj} - q_j \\ \frac{a_{ij} - b_{kj} - q_j}{1} & \text{if } a_{ij} \geq b_{kj} - q_j, \end{cases}$$

where $p_j \geq q_j \geq 0$ indicate the preference and indifference thresholds, respectively. Such thresholds take into account the imprecise criteria evaluations.

The preference threshold represents the smallest difference $a_{ij} - b_k$ compatible with the preference of $a_i$ on criterion $j$, while the indifference threshold indicates the largest indifference $a_{ij} - b_k$ that preserves indifference between $a_i$ and $b_k$. Similarly, the concordance index $C(b_k, a_i)$ can also be defined.
The second phase consists in the discordance test, that is performed by the computation of the discordance index $d_j(a_{ij}, b_k)$ with respect to criterion $j$. Such index is defined as follows:

$$d_j(a_{ij}, b_k) = \begin{cases} 
0 & \text{if } a_{ij} \geq b_{kj} - p_j \\
\frac{b_{kj} - a_{ij} - p_j}{v_j - p_j} & \text{if } b_{kj} - v_j < a_{ij} < b_{kj} - p_j \\
1 & \text{if } a_{ij} \leq b_{kj} - v_j,
\end{cases}$$

where $v_j \geq p_j$ is a veto threshold expressing the smallest difference $a_{ij} - b_k$ which is incompatible with the statement $a_i \succ b_k$.

Finally, a credibility index of the outranking relation is computed by:

$$\sigma(a_i, b_k) = C(a_i, b_k) \prod_{j \in \bar{T}} \frac{1 - d_j(a_{ij}, b_k)}{1 - C(a_i, b_k)},$$

where $\bar{T}$ is the set of criteria such as $d_j(a_{ij}, b_k) > C(a_i, b_k)$. The outranking relation $a_i \succ b_k$ has to be “defuzzyfied” on the the basis of a user-defined threshold $\lambda \in [0.5, 1]$.

The relation $a_i \succ b_k$ is valid if and only if $\sigma(a_i, b_k) > \lambda$. Similarly, the outranking relation $b_k \succ a_i$ is validated if and only if $\sigma(b_k, a_i) > \lambda$.

Choosing a value $\lambda \geq 0.5$, is equivalent to saying that at least 50% of the criteria considered are in favour of the assignment of $a_i$ to class $C_k$.

Then, two assignment procedures could be adopted; the pessimistic and the optimistic ones. The above assignment rules are formulated as follows:

- **Pessimistic assignment** (conjunctive logic): each alternative is compared successively to the profiles $b_{p-1}, b_2 \ldots b_1$; if $a_i \succ b_k$, then $a_i$ is assigned to the category $C_{k+1}$, otherwise $a_i$ is assigned to $C_1$, i.e. the worst category;

- **Optimistic assignment** (disjunctive logic): each alternative being compared to the profiles $b_1, b_2, \ldots, b_{p-1}$; if $b_k \succ a_i \land a_i \nec b_k$, then $a_i$ is assigned to the category $C_k$ and otherwise $a_i$ is assigned to the group $C_p$, i.e. the best category.

Some troublesome situations of incomparability could arise if the two preference statements are verified: $a_i \nec b_k$ and $b_k \nec a_i$.

In the present paper, we adopt the pessimistic rule that is most used in practice, assigning every alternative $a_i$ to the category $C_{k+1}$ if the following inequalities are verified:

$$\sigma(a_i, b_k) \geq \lambda \text{ and } \sigma(b_k, a_i) < \lambda. \quad (1)$$

If there aren’t veto criteria, it is easy to verify that

$$\sigma(a_i, b_k) = C(a_i, b_k) = \sum_{j=1}^{n} w_j c_j(a_i, b_k).$$

As a consequence, the aforementioned decisional rule (1) is simplified as follows:

$$\sum_{j=1}^{n} w_j c_j(a_i, b_k) \geq \lambda \text{ and } \sum_{j=1}^{n} w_j c_j(b_k, a_i) < \lambda. \quad (2)$$
2.2 SMAA-TRI

In this section, we introduce SMAA-TRI, firstly introduced in Tervonen et al., 2007 (see also Tervonen et al., 2009). SMAA-TRI is a SMAA (Stochastic Multicriteria Acceptability Analysis) method that can take into account uncertainty and imprecision on the set of parameters and data required as input by ELECTRE-TRI.

In this paper, SMAA-TRI will be used to analyze the robustness of ELECTRE-TRI based on the parameter stability. By performing Monte Carlo simulations, such a method generates a set of weights on a λ cutting level within an ELECTRE-TRI model.

The input for SMAA-TRI are the following:

- the profiles;
- the feasible set of weights of criteria defined as:

\[ W = \{ w_j \in \mathbb{R}^+ : \sum_{j=1}^{n} w_j = 1 \}; \]
- the λ cutting level;
- the data and the other parameters of ELECTRE-TRI are supposed deterministic.

In SMAA-TRI, a categorization function is defined to evaluate the category \( k \) to which an alternative \( a_i \) is assigned as follows:

\[ k = F(i, \Delta), \quad (3) \]

where \( \Delta \) is the set of parameters of ELECTRE-TRI.

It is also introduced the following category membership function:

\[ m^k_i = \begin{cases} 1, & \text{if } F(i, \Delta) = k \\ 0, & \text{otherwise} \end{cases} \quad (4) \]

The category membership function is used to compute the category acceptability index \( \pi^k_i \) that is numerically a multidimensional integral over the preference parameter space.

The category acceptability index, generally expressed in percentage-wise, evaluates the stability of the assignment of an alternative \( a_i \) to a category \( C_k \). The index is within the range \([0, 1]\); if it results 0, this means that the alternative \( a_i \) is never assigned to category \( C_k \) on the basis of all the parameters randomly generated during the simulations; on the contrary if 1 the alternative \( a_i \) is certainly assigned to category \( C_k \), considering all the parameters randomly generated during the procedure. In this paper, SMAA-TRI has been implemented using JSMAA, an open source software in Java (www.smaa.fi; see Tervonen, 2012). The simulations considered in JSMAA are 10,000.

3 Description of the proposed model

Presently, the starting point of the riskiness evaluation process of an innovative SME is a Business Plan (BP), in which the principal used investment appraisal indicators based on cash-flow estimates, like the Net Present Value (NPV) are computed. In the evaluation process of an innovative SME, such indicators, as it will be shown in the case study, could be useful in a first screening of the enterprise under consideration. In the case study, a scenario analysis has been outperformed by
considering the base-scenario and two worst scenarios to reject eventual unprofitable projects with NPV < 0.

Thus, for each enterprise we have evaluated some financial ratios and then we have compared to the quartiles values for each sector to which the enterprises, considered in the case study, belong. At the same time, we have also estimated their NPV under each scenario.

Besides the need of a preliminary financial analysis, with respect to the innovative SMEs, the only evaluation of the financial factors, estimated in the business plan, is weakly significant, since if their specific risks are not analyzed, their economic-financial prospectives could be affected.

As a consequence, the problem of sorting innovative SMEs by intensity of risk requires to consider several aspects such as multiple criteria; in particular, the non-financial (qualitative) criteria that are the most relevant ones as it has been pointed out in the introduction.

First of all, in a multicriteria problem it is very important to identify all the actors present. The principal actor involved in our decision problem is the credit officer of a bank, that is the Decision Maker (DM). The output of the model will be the sorting of each enterprise to a predefined risk category.

Also, in this decision procedure an important role is also given to the experts, such as engineers, physicists or chemists, that may help the DM in selecting the proper criteria for evaluating an innovative enterprise, especially for detecting its technological risks.

In the present paper, in order to evaluate the riskiness of innovative SMEs, we adopt the multicriteria model, ELECTRE TRI (Yu, 1992), that belongs to the family of ELECTRE methods, firstly introduced in Roy, 1968. Specifically, ELECTRE TRI assigns an innovative SME to some predefined risk categories by comparing it with some reference profiles delimiting the categories.

ELECTRE TRI is implemented within the framework of a constructive approach (Roy, 1993) since its main operational phases are determined by an active participation of the DMs where the DMs’ preferences are not existent in their minds, but they are revealed during an interactive decision process to obtain a final recommendation.

The main phases of the multicriteria judgmental rating model proposed, i.e. ELECTRE-TRI, are listed hereafter:

Phase (i) selection of the evaluation criteria;
Phase (ii) definition of the risk classes;
Phase (iii) elicitation of importance weights of criteria.

Phase (i): selection of the evaluation criteria

Firstly, in a multicriteria problem the alternatives have to be evaluated on the basis of a consistent family of criteria (Roy, 1985), defined as follows:

- two alternatives with the same criteria evaluations have to be assigned to the same risk class (exhaustive criteria);
- an innovative alternative on which a criterion value is decreased in terms of lower risk cannot be assigned to a lower class (consistent criteria);
- an innovative alternative cannot be assigned to a risk class when one criterion is dropped from the family of criteria (non-redundant criteria).

The non-financial criteria, considered in this study, will be gathered in four main groups on the basis of the risk areas specific of an innovation (see Mazzù, 2008). The risk areas considered are described and listed hereafter.
• **Development risk.** The enterprise’s organization shows a weak competence to orient itself to the necessary changes to implement a process or product innovation. Such a risk may be related to some mistakes during the projecting phase of an innovation. Indicators of such a risk may be the management quality, the scientific skills for the patents, or the company profile.

• **Technological risk.** Of course, this risk is crucial for any innovative enterprise. Its weaknesses in the technological skills may result in the failure of the project. The indicators of such a risk are mainly related to the knowledge of the existing technologies or the pros of the technique considered.

• **Market risk.** Such a risk is tied to the continuous monitoring of the potential market and of the key competitors of the innovation under consideration. For example, its possible indicators may be the adoption of customer evaluation models for the innovation’s demand, or knowledge of the competitors.

• **Production risk.** The production of innovation may be affected by the non-flexible company structure. The production risk indicators may be the adequacy of the production structure, dependence on the suppliers for raw materials, and the availability of testing and unit pilots.

Beyond the qualitative criteria (soft information), we have also taken into account some financial criteria estimated on the basis of the Business Plans presented by the enterprises.

In the paper, we have selected two innovation indicators and three financial ratios. With respect to the several innovation indicators available in literature, we have chosen to adopt the two following innovation indicators: Intangible Assets/Fixed Assets (see Brandolini and Bugamelli, 2009) and R&D/Sales (see Kleinknecht et al., 2002). Both indicators are the most used in many empirical studies especially because they are easily measurable.

Concerning the financial ratios, within the multicriteria approach proposed we have considered ROA (profit before taxes/total assets), Short-term debt/Equity, and Cash/Total Asset reflecting the areas of profitability, leverage and liquidity of each enterprise (see Section 4.1. for a full description of the financial analysis).

In financing innovative SMEs, we have taken into account the criteria hierarchically structured as follows:

• at the first level, the criteria have been denoted by $G^r$ where $r = 1, 2, 3, 4, 5$ indicate, respectively, the criteria relative to the development ($G^1$), technological ($G^2$), market ($G^3$) and production ($G^4$) risk areas and financial criteria ($G^5$), i.e. $G = \{G^1, G^2, G^3, G^4, G^5\}$ (see figure 1).

• at the second level, the set of sub-criteria relative to every group of criteria have been considered and denoted by $G^r = \{g^r_1, g^r_2, \ldots, g^r_q, \ldots, g^r_{n_r}\}$ with $q = 1, 2, \ldots, n_r$. 

![Figure 1: A hierarchical family of criteria in the risk evaluation of an innovative SME.](image-url)
At this level, we have denoted the set of all the sub-criteria by $G$ where $|G| = n = n_1 + n_2 + n_3 + n_4 + n_5$.

For the sake of simplicity, $g_{(j)}$ has been used to indicate any sub-criterion belonging to $G$ with $j = 1, 2, \ldots, n$. As is well-known (see Figueira et al., 2010), the ELECTRE methods require that all the criteria are defined on a common level; henceforth we consider the criteria at the second level.

3.1 Phase (ii): definition of the risk classes

Within ELECTRE-TRI, the reference profile, delimiting the risk categories, is given by the vector $b_k = \{b_{k1}, b_{k2}, \ldots, b_{kj}\}$, $j$ being the criterion index and whose coordinates indicate the performance of the profile in each of its criteria. It delimits the lower limit of category $C_{k+1}$ and the upper limit of category $C_k$. Delimiting the risk classes is also a DM’s task. Determining categories depends on the DM, how (s)he perceives the different criteria evaluated on the basis of the alternatives under consideration. In the case study presented in Section 4, the loan officers of the Italian bank interviewed have suggested us to adopt five rating classes expressing a decreasing order of risk from the highest level risk (risk class 1: bad enterprises) to the lowest (risk class 5: very good enterprises).

3.2 Phase (iii): the importance weights of criteria

One of the most important and difficult tasks of MCDA is the determination of importance weights of criteria. In literature, several methods have been proposed to assess weights of criteria (see, for example Bana e Costa and Vansnick, Bana e Costa and Vansnick, 1997, Jacquet-Lagrèze and Siskos, 1982 and Mousseau et al., 2001).

In addition to the different preference models of elicitation of weights, an important question in MCDA is the relative importance of criteria (see Mousseau, 1995 and Roy and Mousseau, 1996). Indeed, there is a different meaning between weights in compensatory methods, like the Multi-Attribute Utility Theory (MAUT) (Keeney and Raiffa, 1976) and non-compensatory methods like ELECTRE (Roy, 1991) and PROMETHEE (Brans et al., 1984). In compensatory methods, weights of criteria are essentially trade-offs between criteria and are constants dependent on their scale and range. On the other hand, in non-compensatory methods the weights of criteria have an intrinsic value and do not change on the basis of the scale of criteria used.
Among these, we recall the revised Simos’ method (Roy and Figueira, 2002), known also as the cards method, that has been used in the case study illustrated in the next section.

Within the Simos’ procedure, the DM ranks the criteria from the least to the most important by using a set of cards (one for each criterion). The DM can also insert some blank cards to separate the relative importance between criteria. If the DM inserts no white cards between criteria, this means that these criteria have not the same weights and their relative difference can be taken as unit measure \( u \) for weights. With a similar reasoning, if the DM inserts one white card, two white cards, etc, this means respectively a difference of weights of two times \( u \), three times \( u \), etc.

In the next section, where a case study is presented, the cards method has been adopted to obtain ordinal information on the weights of the criteria and then to obtain indirectly the weights of criteria from the DM’s ranking.

Within the case study, we have considered different loan officers as it is supported by the literature that has investigated the role of the loan officers in lending decision making in banks (see for example Tronnberg and Hemlin, 2014 that examines the organizational factors that influence bank loan officers). Specifically, we have interviewed five loan officers of one of the main Italian banks, which have given different orders of importance of weights of criteria depending on their preference attitudes.

In Section 4.4, a case study has been carried by taking into account the different DMs interviewed. For each DM, we have applied SMAA-TRI by varying the \( \lambda \)-cutting level represented by a stochastic variable uniformly distributed. Then, to take into account simultaneously all the DMs’ sets of weights, the evaluation of each criterion ranges in an interval delimited by the maximum and the minimum weight for all DMs. Since the sets of weights are imprecise, we have outperformed again SMAA-TRI, computing the category acceptability indices for each alternative.

4 Start-up case study

In this section, we carry out a real case study regarding four innovative SMEs, headquartered in Italy, that we have contacted asking them their business plans and to fill out a structured questionnaire. The data collected in the questionnaire concern some information on the company, distribution and customer networks, demand forecasting, supply chain information, the owners’ Company CV and eventual awards received by the company. For the sake of privacy, we have renamed the companies as A, B, C and D. Moreover, we have interviewed five loan officers of one of the main Italian banks to simulate the financing of such companies on the basis of the multicriteria rating model proposed in Section 3. Hereafter, we report a brief description of the considered companies.

Companies

1. Company A is a biotechnological start-up, operating in the field of the green economy. It has developed some biological systems based on plants and micro-organisms forming some eco-friendly barriers, to prevent soil from the hydrological destruction and the environmental pollution. The services provided by it, consist of realizing such biological barriers, also giving consultancy; furthermore its services are offered at lower prices than the ones of the traditional techniques.

2. Company B is a technological company with a strong expertise in digital communications. The innovative idea of the company is to develop a “Water-MeMo” that is a wireless sensor network for water leakage detection, based on energy harvesting. In particular, its technology can be applied not only in the water distribution field, but also in other energy applications, such as heat and gas, or environmental monitoring. Its main innovation is in the green technology
FluE (Fluid Energy) that is based on some sensors auto-charged by the energy produced by the fluid itself through some piezoelectric foils.

3. Company C is a high-technological start-up, an R & D mechanical design and service provider company with a focus on material recovery systems applied to thin-film deposition processes. Its mission is providing breakthrough technology, in order to increase the efficiency of PVD (Physical Vapour Deposition) processes, today used to produce microchips, MEMS (Micro Electro-Mechanical Systems), solar cells and other hi-tech devices.

4. Company D is a high-technological start-up that aims to produce and commercialize graphene and carbon nanotubes for industrial use and for research, to develop new materials based on nano-particles and provide technical assistance and advice to businesses willing to use these technologies. The company is mainly focused in producing nano-engineered epoxy resins used in the manufacture of sport equipment, for example sailing boats or kiteboards.

4.1 Financial analysis

The starting point of the financial analysis, presented in this section, is the enterprises’ business plan, on which we have out-performed a scenario analysis. From the base-case scenario, we have developed two different worst scenarios considering the cash-flows lowered by 20% and 40%.

First of all, we have evaluated the NPVs for each scenario since this is a screening tool to know if the projects are profitable. The NPV under the different scenarios have been computed by using a risk free rate of 7.93%, commensurate with the performance of Italian public debt securities in date 30/9/2012 (Base informativa pubblica, Banca d’Italia, 2013). The results are reported for each enterprise in Table 12 of the Appendix A. In all the enterprises under each scenario, all the NPVs result positive and consequently all the projects are profitable. Then, we have computed some financial ratios.

First of all, let us remark that the enterprises have considered different planning horizons; Company D has presented a three years BP, Company A a four year BP, Company B has considered a five years BP and Company C a six years BP. Even if track records of innovative firms are not available, we have evaluated some financial ratios of the enterprises of the case study on the basis of their business plan. On the basis of the available financial data, the following financial ratios have been selected: ROA, Short-term debt/Equity, and Cash/Total Asset, reflecting respectively the areas of profitability, leverage and liquidity of each enterprise (these ratios have been already selected to evaluate the US SMEs in the paper of Altman and Sabato, 2007).

To the aim of detecting the Italian firms in the same sector of the four enterprises under evaluation, we have considered their ATECO codes which are used to classify companies based on their activities. From AIDA dataset, we have reported the financial ratios of the balance-sheets of the sectors of companies A, B, C and D respectively, composed of 515, 13,735, 1,001, and 1,122 SMEs (enterprises with a number of employees lower than 250) over the period 2008-2012.

Finally, from 2008 to 2012 we have evaluated the quartiles of each financial ratio for all the enterprises in the sample. The quartiles with respect to each sector has been assumed as the limit profiles in performing the multicriteria model of ELECTRE-TRI (see Table 13).

4.2 Phase (i): building a family of criteria

Since most of the criteria, considered in this paper, are qualitative, for a few of them it has been natural to adopt a binary codification while for most of them, for simplicity, we have used the same ordinal scale on a five point scale. Let also note that all the criteria evaluations are increasing, i.e. the more the better excepting the Short-term debt/Equity that has to be minimized.
The family of criteria have been elaborated by the credit officers interviewed with the help of the experts. Even more on the basis of the BP presented by the firms, the criteria evaluations have been given by the credit officers in cooperation with the experts that can detect the specific risks of each enterprise. The criteria considered in the case study are described hereafter (see also Table 1 for an overview of the criteria).

Criteria related to the development risk.

$[g^1_{(1)}]$ Awards: a five-points scale is adopted, ranging from one point, if a company hasn’t received no award, to five points, if the innovative enterprise has received an international award.

The idea of Company A has been certified by different awards. Among others the D2T Start Cup given by Trentino Sviluppo and it has also been classified first in the competition AGRIs-tart Up. On the basis of such criterion, the DMs suggest an evaluation of four points.

Company B has obtained the following awards: research grant Working Capital 2011, seed fund eCapital 2011 and ItaliaCamp 2012. On the basis of such criterion, four points have been given to Company B.

Even Company C has received different awards: both Italian and international. Among others Company C has obtained the third place in the Innovact Campus Award 2012 in Reims (France). On the basis of such criterion, five points have been given to Company C.

Company D won the Business Plan Competition eCapital 2010, competition aimed at creating innovative startups. In 2011, it was finalist at the Italian National Innovation Award “PNI - Telecom Working Capital”. On the basis of such criterion, four points have been given to Company C.

$[g^1_{(2)}]$ Scientific skills: a five-points scale is adopted, ranging from one point, if the principal partners have no specific studies, to five points, if the owners of the innovative enterprise have received a PHD and have some specific job experiences.

Company A. The three principal partners are agronomists and are specialized in microbiology and in plant genetics. Company A has received three points on this criterion.

Company B is composed of three young engineers, a full professor, a strategic marketing expert and ArieLab s.r.l., a spin-off of the University Politecnica delle Marche. Company B has received five points on this criterion.

Company C. The management team is composed of a well qualified staff. For example, the CEO has a Master degree in Engineering, or the CTO has a Master degree in Physics and NanoScience. The DMs have given three points on this aspect.

Company D. All the five members are well qualified; some of them have a degree in engineering, others are specialized in nanotechnology and one of them is specialized in sailing prototypes that are the main products in which the company is investing its research and sale activities. The DMs have given five points on this criterion.

Criteria related to the technological risk.

$[g^2_{(3)}]$ Pros of the techniques used in comparison to other similar already existing: a five-points scale is adopted; one point means that the advantages are irrelevant, while five point levels are given if they are significant.

Company A has received three points, since there are other methods that can be used to prevent soil from the hydrological destruction and the environmental pollution.
On the basis of this criterion, Company B has received five points since the only similar existing technique consists of putting a few Data Loggers in some points of the water pipelines to register the noise by a microphone. Anyway, such products are too expensive and detect the soundness of the water distribution una tantum.

On the basis of this criterion, Company C has received five points since other existing techniques need too complex chemical processes to recover precious materials.

Company D has received three point levels, since the retail prices of their epoxy resins are too high in comparison to other existing ones.

Criteria related to the market risk.

$[g^3_{(4)}]$ Presence of key competitors: a five-points scale is adopted, ranging from one point, if there is a monopolist competitor in the market, to five points, if the innovative enterprise is the only one competitor present in the market.

Company A has one competitor, that adopts a methodology much more expensive and with many different drawbacks, for example the plants used are not very suitable for the soil. Consequently, on the basis of such criterion Company A has obtained an evaluation of four points.

Company B doesn’t have competitors in the market. The only similar solution, i.e. the Data Logger has many drawbacks. The DMs suggest an evaluation of five points on this criterion.

Even if Company C has registered a patent, this doesn’t represent a barrier to avoid that other enterprises could enter the market, by slightly modifying the system developed by Company C. Some possible similar solutions could be: vacuum ad hoc chambers, static monitors and mechanical removing. Anyway, the above techniques need the support of complex chemical processes. On the basis of such criterion, The DMs suggest an evaluation of two points.

Company D has different competitors in nanotechnology even if operating with different prices and quality in their products. The DMs give an evaluation of two points on the basis of this criterion.

$[g^3_{(5)}]$ Potential market: a five-points scale is adopted; a one point means that the market is reducing while 5 means that the market is booming.

Company A’s potential market is limited by the traditional techniques, mainly based on chemical products, preferred to the innovative solution offered by Company A. In fact, there is a cultural resistance to accept this new type of methodology to prevent soil from the hydrological destruction and the environmental pollution, even if nowadays there is much more attention to environmental problems. On the basis of this criterion, a prudential evaluation of three has been considered.

With respect to this point, the DMs believe that the Company B’s market is reducing (1 point). More precisely, even if the private and public companies running the water distribution in Italy need a system to monitor the water leakage, they are not financially sound.

Company C. The market of thin film deposition is booming, with an estimation of market value amounting to 22.4 billion USD in 2015. The use of precious materials (Au, Ag, Pt and Pd) is very common in optics and electronics. On this criterion, Company C has received an evaluation of five points.

Company D. Within the nanotechnology market nanomaterials are a booming business with benefits for all other sectors. Carbon nanotubes are in this case, together with some materials connected to them (e.g. graphene and fullerenes), the most important products of the entire sector. On this criterion, Company D has received an evaluation of five points.
Criteria related to the production risk.

\[ g^4_{(6)} \] Availability of testing and unit pilots: codes yes (1) or no (0).

Company A has not yet realized any pilot installations that can be useful to show to the potential clients the advantages of the technique proposed compared to the traditional ones.

Company B hasn’t yet produced any unit pilots, even if it is one of its immediate projects.

Company C has developed a first prototype and tested it in the vacuum chamber of a thermal evaporator at the laboratory of CNR.

The Company D’s has started a pilot plant for the supplement of nanocarbons filler to thermosetting epoxy resins.

\[ g^4_{(7)} \] Owner of a patent: codes yes (1) or no (0).

Company A hasn’t yet applied for a patent even if it is one of its projects.

Company B hasn’t yet registered the patent for the FluE sensor, even if it is one of its goals.

The Company C has a right of an Italian patent entitled: \textit{Palette system for the recovery of metals from thin-film deposition facilities} and also of an International application entitled: \textit{Palette modular device for collection of metals in this film deposition equipment}.

The Company D’s hasn’t yet applied for a patent, but it aims to record strategic patents on its core product and a series of multiple patents that go to cover similar areas of research and development thus protecting future market segments.

Financial criteria

\[ g^5_{(8)} \] Intangible Assets/Fixed Assets.

\[ g^5_{(9)} \] R&D/Sales.

\[ g^5_{(10)} \] ROA.

\[ g^5_{(11)} \] Short-term debt/Equity.

\[ g^5_{(12)} \] Cash/Total Asset.

Summing up, for each enterprise the scores on the considered criteria are showed in Table 2.

4.3 Phase (ii): determining the limit profiles

The limit profiles are built by the DMs who determine the performance on each criterion with respect to every category. The DMs have considered four common limit profiles with respect to the qualitative criteria (see Table 3).

Instead, concerning the financial criteria, they have selected a different set of limit profiles for each enterprise under consideration (see Table 4). Such choice has been justified by considering that each enterprise belongs to a sector different from the others. Every sector is characterized by a specific financial risk. As explained in Section 4.1 we have considered the Italian firms in the same sector of the four enterprises under evaluation on the basis of their ATECO codes. We have calculated the quartiles of each financial criterion for all the enterprises in the sample. The quartiles with respect to each sector have been adopted as the limit profiles in performing the multicriteria model of ELECTRE-TRI. The upper bound of the less risky category \( C_5 \) has been estimated by considering the maximum of every criterion with respect to all sectors. Only the limit profiles for R&D have been elaborated by the DMs and are the same for all the sectors.

For simplicity, the preference and indifference thresholds have been set equal to zero.
Table 1: Family of criteria

| $G^1$: development risk | Codes |
|-------------------------|-------|
| $g_{1}^{(1)}$: awards   | no awards (1) |
|                         | municipal (2) |
|                         | regional (3) |
|                         | national (4) |
|                         | international (5) |

| $g_{1}^{(2)}$: scientific skills | Codes |
|---------------------------------|-------|
| no skills (1)                   | degree (2) |
|                                | master (3) |
|                                | PHD (4) |
|                                | PHD+Work experiences (5) |

| $G^2$: technological risk | Codes |
|---------------------------|-------|
| $g_{2}^{(3)}$: pros of the technique | irrelevant (1) |
|                                | weakly significant (2) |
|                                | significant (3) |
|                                | strongly significant (4) |
|                                | very significant (5) |

| $G^3$: market risk | Codes |
|-------------------|-------|
| $g_{3}^{(4)}$: key competitors | monopolist (1) |
|                                | numerous competitors (2) |
|                                | few competitors (3) |
|                                | one competitor (4) |
|                                | start-up (5) |

| $g_{3}^{(5)}$: potential market | Codes |
|---------------------------------|-------|
| reducing (1)                    | static (2) |
|                                | weakly rising (3) |
|                                | rising (4) |
|                                | booming (5) |

| $G^4$: production risk | Codes |
|------------------------|-------|
| $g_{4}^{(6)}$: availability of testing and unit pilots | no (0), yes (1) |
| $g_{4}^{(7)}$: owner of a patent | no (0), yes (1) |

| $G^5$: Financial criteria | unit |
|---------------------------|------|
| $g_{5}^{(8)}$: intangible assets/fixed assets | percentage |
| $g_{5}^{(9)}$: R&D/sales | percentage |
| $g_{5}^{(10)}$: ROA | percentage |
| $g_{5}^{(11)}$: Short term debt/Equity | percentage |
| $g_{5}^{(12)}$: Cash/Total Asset | percentage |

4.4 Phase (iii): eliciting the set of weights

Let us assume a total preorder $\preceq$, i.e., a reflexive binary relation on the set of criteria $G$ satisfying two additional properties: transitivity and completeness. In this case, the preference relation can be decomposed into its symmetric part $\sim$, called *indifference*, and into its asymmetric part $\prec$, called *strict preference*, whose semantics are, in a multicriteria context, respectively:

- $g_{j_1}^{(r_1)} \sim g_{j_2}^{(r_2)} \iff g_{j_1}^{(r_1)}$ is equally important to $g_{j_2}^{(r_2)}$,
- $g_{j_1}^{(r_1)} \prec g_{j_2}^{(r_2)} \iff g_{j_1}^{(r_1)}$ is less important than $g_{j_2}^{(r_2)}$,

where $g_{j_1}^{(r_1)}$ and $g_{j_2}^{(r_2)}$ are two distinct criteria from the set $G$.

Table 2: Evaluation matrix.

| Company | $g_{1}^{(1)}$ | $g_{1}^{(2)}$ | $g_{3}^{(3)}$ | $g_{4}^{(4)}$ | $g_{5}^{(5)}$ | $g_{1}^{(6)}$ | $g_{2}^{(7)}$ | $g_{1}^{(8)}$ | $g_{1}^{(9)}$ | $g_{10}^{(10)}$ | $g_{11}^{(11)}$ | $g_{12}^{(12)}$ |
|---------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|----------------|----------------|---------------|
| A       | 4             | 3             | 3             | 4             | 3             | 0             | 0             | 0.55          | 0.06          | 0.24           | 0.18           | 0.74           |
| B       | 4             | 5             | 5             | 5             | 1             | 0             | 1             | 0.72          | 0.17          | 0.03           | 0.12           | 0.51           |
| C       | 5             | 3             | 5             | 2             | 5             | 1             | 1             | 0.18          | 0.05          | 0.94           | 0.3            | 0.56           |
| D       | 4             | 5             | 3             | 2             | 5             | 1             | 0             | 0.06          | 0.14          | 0.52           | 0.11           | 0.26           |
Table 3: Limit profiles with respect to the qualitative criteria.

|       | $g_1$ | $g_2$ | $g_3$ | $g_4$ | $g_5$ | $g_6$ | $g_7$ |
|-------|-------|-------|-------|-------|-------|-------|-------|
| $b_1$ | 1     | 1     | 1     | 1     | 0     | 0     |       |
| $b_2$ | 2     | 2     | 2     | 2     | 0     | 0     |       |
| $b_3$ | 3     | 3     | 3     | 3     | 0     | 1     |       |
| $b_4$ | 4     | 4     | 4     | 4     | 1     | 1     |       |

Table 4: Limit profiles with respect to the financial criteria

(a) Company A

|       | $g_8$ | $g_9$ | $g_{10}$ | $g_{11}$ | $g_{12}$ |
|-------|-------|-------|-----------|-----------|-----------|
| $b_1$ | 0     | 0.03  | -0.03     | 5.44      | 0.02      |
| $b_2$ | 0.01  | 0.05  | 0.01      | 1.42      | 0.07      |
| $b_3$ | 0.2   | 0.07  | 0.05      | 0.14      | 0.18      |
| $b_4$ | 1.34  | 0.1   | 0.1       | 0.14      | 0.21      |

(b) Company B

|       | $g_8$ | $g_9$ | $g_{10}$ | $g_{11}$ | $g_{12}$ |
|-------|-------|-------|-----------|-----------|-----------|
| $b_1$ | 0     | 0.03  | -0.01     | 3.72      | 0.01      |
| $b_2$ | 0.17  | 0.05  | 0.03      | 1.22      | 0.06      |
| $b_3$ | 1.34  | 0.07  | 0.09      | 0.31      | 0.16      |
| $b_4$ | 1.34  | 0.1   | 0.1       | 0.14      | 0.21      |

(c) Company C

|       | $g_8$ | $g_9$ | $g_{10}$ | $g_{11}$ | $g_{12}$ |
|-------|-------|-------|-----------|-----------|-----------|
| $b_1$ | 0     | 0.03  | -0.01     | 3.14      | 0.01      |
| $b_2$ | 0.09  | 0.05  | 0.04      | 1.07      | 0.06      |
| $b_3$ | 0.43  | 0.07  | 0.28      | 0.16      |           |
| $b_4$ | 1.34  | 0.1   | 0.1       | 0.14      | 0.21      |

(d) Company D

|       | $g_8$ | $g_9$ | $g_{10}$ | $g_{11}$ | $g_{12}$ |
|-------|-------|-------|-----------|-----------|-----------|
| $b_1$ | 0     | 0.03  | -0.04     | 2.55      | 0.03      |
| $b_2$ | 0.07  | 0.05  | 0         | 0.67      | 0.08      |
| $b_3$ | 0.91  | 0.07  | 0.04      | 0.14      | 0.21      |
| $b_4$ | 1.34  | 0.1   | 0.1       | 0.14      | 0.21      |

In the following, we report the preference orders of five credit officers of one of the main Italian bank interviewed within the case study.

For the first DM (DM1, say), the most important criterion assumed in the evaluation of an innovative enterprise has been the existence of a unit pilot and the second most important criterion has been the patent.

DM1 has given this preference information on the criteria:

$g_1 \sim g_2 \prec g_5 \sim g_9 \prec g_3 \sim g_4 \sim g_7 \prec g_6 \prec g_3$. 

The second DM (DM2, say) has expressed these preference statements:

$g_4 \prec g_5 \sim g_9 \prec g_1 \sim g_2 \sim g_7 \sim g_10 \sim g_11 \sim g_12 \prec g_3 \prec g_4 \prec g_7 \prec g_6 \prec g_3$. 

In this case, the prevailing criteria in evaluating an innovative enterprise have been the potential market and the presence of key competitors, i.e. the sub-criteria relative to the risk market.

The DM3’s preference information has been the following:

$g_3 \sim g_5 \prec g_8 \prec g_4 \sim g_7 \prec g_6 \prec g_1 \sim g_2 \prec g_5 \sim g_10 \sim g_11 \sim g_12 \prec g_3$. 

In this case, the most important weights considered by the DM3 have been the sub-criteria relative to the technological risk and the second ones the financial ratios.

The DM4’s preference information has been given by:

$g_4 \sim g_5 \prec g_8 \prec g_1 \sim g_2 \prec g_3 \prec g_6 \prec g_10 \sim g_11 \sim g_12 \prec g_3 \prec g_5 \prec g_7$. 

In this case, the most important criterion is assumed to be the patent’s ownership and the second most important one is the potential market. The DM5’s preference information has been:
\[ g_{(1)}^1 \sim g_{(2)}^1 \prec g_{(6)}^4 \prec g_{(4)}^3 \prec g_{(5)}^3 \prec g_{(7)}^4 \prec g_{(8)}^5 \prec g_{(9)}^5 \prec g_{(10)}^5 \sim g_{(11)}^5 \sim g_{(12)}^5. \]

In the last case, the most important criteria have been the financial ones.

In all the five DMs, the criteria \((g_{(1)}^1, g_{(2)}^1), (g_{(10)}^5, g_{(11)}^5)\) and \((g_{(13)}^5, g_{(14)}^5, g_{(15)}^5)\) have been considered equally important.

As explained in Section 3.2, the method adopted to assess the criteria weights is the Simos’ procedure (the computations relative to the DM1’s weights are reported in the Appendix). For all the DMs, the criteria weights obtained are showed in Table 5.

Table 5: Weights for each DM.

| DM1     | \(g_{(1)}^1\) | \(g_{(2)}^1\) | \(g_{(3)}^5\) | \(g_{(4)}^3\) | \(g_{(5)}^3\) | \(g_{(6)}^4\) | \(g_{(7)}^4\) | \(g_{(8)}^5\) | \(g_{(9)}^5\) | \(g_{(10)}^5\) | \(g_{(11)}^5\) | \(g_{(12)}^5\) |
|---------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| DM2     | 0.0250        | 0.0250        | 0.1650        | 0.0560        | 0.1960        | 0.1810        | 0.0400        | 0.0400        | 0.0720        | 0.0720        | 0.0720        | 0.0720        |
| DM3     | 0.0530        | 0.0530        | 0.0934        | 0.1740        | 0.1640        | 0.0230        | 0.0330        | 0.0330        | 0.0632        | 0.0632        | 0.0632        | 0.0632        |
| DM4     | 0.1120        | 0.1120        | 0.1390        | 0.0190        | 0.0190        | 0.0720        | 0.0600        | 0.0600        | 0.1250        | 0.1250        | 0.1250        | 0.1250        |
| DM5     | 0.0330        | 0.0330        | 0.1490        | 0.0540        | 0.1600        | 0.0640        | 0.1700        | 0.0230        | 0.0230        | 0.0970        | 0.0970        | 0.0970        |

4.5 Computing the category acceptability indices

In this section, we have computed the category acceptability indices, according to the different DMs, by using the JSMAA software (the results are showed in Table 6). In all the computations, the \(\lambda\)-cutting level has been represented by a stochastic variable uniformly distributed in the range \([0.65, 0.85]\).

Table 6: Category acceptability indices according to the different DMs.

(a) DM1

| Company | \(C_1\) | \(C_2\) | \(C_3\) | \(C_4\) | \(C_5\) |
|---------|--------|--------|--------|--------|--------|
| A       | 0%     | 0%     | 36%    | 64%    | 0%     |
| B       | 0%     | 0%     | 0%     | 74%    | 26%    |
| C       | 0%     | 0%     | 0%     | 11%    | 89%    |
| D       | 0%     | 0%     | 63%    | 37%    | 0%     |

(b) DM2

| Company | \(C_1\) | \(C_2\) | \(C_3\) | \(C_4\) | \(C_5\) |
|---------|--------|--------|--------|--------|--------|
| A       | 0%     | 0%     | 0%     | 100%   | 0%     |
| B       | 0%     | 17%    | 18%    | 65%    | 0%     |
| C       | 0%     | 0%     | 46%    | 31%    | 23%    |
| D       | 0%     | 40%    | 47%    | 13%    | 0%     |

(c) DM3

| Company | \(C_1\) | \(C_2\) | \(C_3\) | \(C_4\) | \(C_5\) |
|---------|--------|--------|--------|--------|--------|
| A       | 0%     | 0%     | 0%     | 100%   | 0%     |
| B       | 0%     | 0%     | 0%     | 0%     | 100%   |
| C       | 0%     | 0%     | 0%     | 46%    | 54%    |
| D       | 0%     | 0%     | 0%     | 57%    | 43%    |

(d) DM4

| Company | \(C_1\) | \(C_2\) | \(C_3\) | \(C_4\) | \(C_5\) |
|---------|--------|--------|--------|--------|--------|
| A       | 0%     | 0%     | 23%    | 77%    | 0%     |
| B       | 0%     | 5%     | 14%    | 33%    | 48%    |
| C       | 0%     | 0%     | 0%     | 0%     | 100%   |
| D       | 0%     | 0%     | 49%    | 51%    | 0%     |

(e) DM5

| Company | \(C_1\) | \(C_2\) | \(C_3\) | \(C_4\) | \(C_5\) |
|---------|--------|--------|--------|--------|--------|
| A       | 0%     | 0%     | 27%    | 73%    | 0%     |
| B       | 0%     | 0%     | 22%    | 18%    | 60%    |
| C       | 0%     | 0%     | 69%    | 20%    | 11%    |
| D       | 0%     | 0%     | 55%    | 45%    | 0%     |
4.6 Category results

In Table 7, we have reported the highest category acceptability for each DM obtained during the simulations. One can notice that the assignment of Company A to the category $C_4$ is very stable since all the DMs agree with the same assignment. Company B is assigned to category $C_5$ by all the DMs except for the DM1. So alternative B has been sorted in category $C_5$. Company C is assigned to category $C_5$ by three DMs while the highest category acceptabilities for DM2 and DM5 are obtained, respectively, for the classes $C_4$ and $C_3$ even if DM2 and DM5 have a non zero probability of assignment of Company C to $C_5$ equal, respectively, to 23% and 11%. Thus, alternative C has been assigned to category $C_5$.

Company D is assigned to category $C_3$ by three DMs, since DM3 and DM4 slightly disagree on this assignment. But the DM4 has a very high probability (49%) to assess Company D to category $C_3$ (see Table 6), so the DM4 almost agrees with the other DMs. Consequently, Company D has been assigned to category $C_3$.

| Company | DM1 | DM2 | DM3 | DM4 | DM5 | Category Result |
|---------|-----|-----|-----|-----|-----|-----------------|
| A       | $C_4$ (64%) | $C_4$ (100%) | $C_4$ (100%) | $C_4$ (77%) | $C_4$ (73%) | $C_4$           |
| B       | $C_4$ (74%) | $C_4$ (65%) | $C_5$ (100%) | $C_5$ (48%) | $C_5$ (60%) | $C_5$           |
| C       | $C_5$ (89%) | $C_4$ (46%) | $C_5$ (100%) | $C_5$ (100%) | $C_3$ (69%) | $C_5$           |
| D       | $C_3$ (63%) | $C_3$ (47%) | $C_4$ (57%) | $C_4$ (51%) | $C_3$ (55%) | $C_3$           |

To avoid these conflict situation among the DMs, we consider, as already done in the paper by Morais et al., 2012, the minimum and the maximum weight for each criterion for all the DMs.

In this way, the weight of each criterion ranges in an interval reflecting all the DMs’ attitudes. The results obtained are showed in Table 8.

| Company | Class 1 | Class 2 | Class 3 | Class 4 | Class 5 | Category Result |
|---------|---------|---------|---------|---------|---------|-----------------|
| A       | 0%      | 0%      | 10%     | 90%     | 0%      | $C_4$           |
| B       | 0%      | 6%      | 20%     | 34%     | 40%     | $C_5$           |
| C       | 0%      | 0%      | 31%     | 35%     | 34%     | $C_5$           |
| D       | 0%      | 0%      | 40%     | 50%     | 10%     | $C_4$           |

By performing again the JSMAA software, we have computed the category acceptabilities presented in Table 8(b) (see also Figure 3 for a representation of category acceptabilities in terms of an histogram).

Looking at Table 8(b), the assignments of companies A and B are the same given at an individual level (see Table 7). Instead, the category results of Companies C and D are not very stable at a group level. Considering Company C, Table 8(b) shows two similar probabilities of assignment to classes $C_4$ (35%) and $C_5$ (34%), but the DMs have decided to assign Company C to class $C_4$ giving more relevance to the individual level. The same reasoning can be done for Company D. From Table 7 Company D is assigned to class $C_4$ (50%), even if there is a high probability (40%) which assigns Company D to class $C_3$. 

Table 7: Results of SMAA-TRI for each DM with $\lambda$ varying in the range $[0.65, 0.85]$.

| Company | DM1 | DM2 | DM3 | DM4 | DM5 | Category Result |
|---------|-----|-----|-----|-----|-----|-----------------|
| A       | $C_4$ (64%) | $C_4$ (100%) | $C_4$ (100%) | $C_4$ (77%) | $C_4$ (73%) | $C_4$           |
| B       | $C_4$ (74%) | $C_4$ (65%) | $C_5$ (100%) | $C_5$ (48%) | $C_5$ (60%) | $C_5$           |
| C       | $C_5$ (89%) | $C_4$ (46%) | $C_5$ (100%) | $C_5$ (100%) | $C_3$ (69%) | $C_5$           |
| D       | $C_3$ (63%) | $C_3$ (47%) | $C_4$ (57%) | $C_4$ (51%) | $C_3$ (55%) | $C_3$           |

Table 8: Results of SMAA-TRI by considering all the DMs.

(a) Interval weights.

| $g_{i1}$ | $g_{i2}$ | $g_{i3}$ | $g_{i4}$ | $g_{i5}$ | $g_{i6}$ | $g_{i7}$ | $g_{i8}$ | $g_{i9}$ | $g_{i10}$ | $g_{i11}$ | $g_{i12}$ |
|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| [0.022, 0.112] | [0.022, 0.112] | [0.0934, 0.165] | [0.0190, 0.174] | [0.0190, 0.184] | [0.035, 0.196] | [0.023, 0.184] | [0.023, 0.112] | [0.023, 0.112] | [0.0632, 0.125] | [0.0632, 0.125] | [0.0632, 0.125] |

(b) Category acceptability indices.

| Company | Class 1 | Class 2 | Class 3 | Class 4 | Class 5 | Category Result |
|---------|---------|---------|---------|---------|---------|-----------------|
| A       | 0%      | 0%      | 10%     | 90%     | 0%      | $C_4$           |
| B       | 0%      | 6%      | 20%     | 34%     | 40%     | $C_5$           |
| C       | 0%      | 0%      | 31%     | 35%     | 34%     | $C_5$           |
| D       | 0%      | 0%      | 40%     | 50%     | 10%     | $C_4$           |
The elaboration of the category acceptabilities and the sorting results have shown some weaknesses of companies C and D. In the following section, we will show how the proposed multicriteria model can be used as a risk assessment tool to reveal such behaviors and detect the risk factors that can affect the creditworthiness of a company.

Furthermore, it is also worthy to notice that the proposed credit model can involve some type I and II errors. The type I and type II errors evaluated in every credit risk model can be interpreted in our model in this way. The assignment to an ordered class gives a judgment on the creditworthiness of the enterprises. For example, in our case study classes with the low level of risk are the classes 4 and 5. Consequently, if an alternative \( i \) is assigned to class 4 or 5, in our model the type I error refers to the classification of a low risk company as a high risk company in all the simulations outperformed. Thus, the error of type I can be evaluated by the sum of the category acceptabilities \( \pi_1^i, \pi_2^i \) and \( \pi_3^i \). Conversely, if an alternative \( i \) is assigned to class 1, 2 or 3, in our model the type II error refers to the classification of high risk firms as low risk firms considering all the simulations. Thus, the error of type II can be considered as the sum of the category acceptabilities \( \pi_4^i \) and \( \pi_5^i \). For example, if an alternative \( i \) has a \( \pi_4^i = 90\% \) and \( \pi_2^i = 3\% \) and \( \pi_3^i = 7\% \), this means that alternative \( i \) is sorted to category \( C_4 \), observing a type I error equal to 10%.

5 Discussion and managerial implications

On the basis of the results obtained in the previous section, some observations can be done.

From Table \( \text{Table 8} \) one could observe that some inconsistencies could be detected comparing the results obtained from the aggregation process of all the DMs, based on a common set of intervals of the weights, to those of the individual DMs shown in Table \( \text{Table 6} \). For instance, is it possible that the aggregate acceptability index for a particular category is positive even if all the corresponding individual indices are zero (and vice versa). As an example take Company D: in Table \( \text{Table 8} \) the acceptability index for class \( C_5 \) is 10% even though for 4 of the 5 DMs the indices are zero. On the other hand, take Company B the acceptability index for class \( C_2 \) is only 6%, but again for 3 of the 5 DMs the indices are 0%. These eventual conflict situations can be explained as follows. Since for each DM a different set of weights has been adopted, in many cases such as in the example of Company B there isn’t a consensus of majority of DMs to determine the risk class.

It is worthy to notice that the category acceptability indices could exhibit some ”non-monotonic” behavior. For instance, take Company D and suppose to improve the evaluation on the criterion \( g_3^2 \) by giving a qualitative score equal to 4.
In this case, for the DM5 Company D will be assigned either in class $C_3$ or class $C_5$, respectively, with acceptabilities indices of 63% and 47%.

In fact, for example take Company D and the DM5, in this case it results that $\sigma(D, b_3) = \sigma(D, b_4) = 0.666$ and $\sigma(b_3, D) = \sigma(b_1, D) = 0.26$. From a technical point, such behavior can be explained by the special features of the ELECTRE methods. Since Company D overcomes both the profiles $b_3$ and $b_4$, the indices aforementioned are equal. Then, the assignment of Company D to class $C_3$ or $C_5$ depends on the choice of $\lambda$, expressing the level of credibility with which a company is assigned to a class or to another. Analyzing the credit granting process, this phenomenon implies that some criteria are the risk factors which influence the success of a project. Coming back to the example, the most critical element is the criterion key competitors which is at a level below the profile $b_3$. Even more a company exhibiting a "non-monotonic" behavior, it’s more fragile from a credit risk point of view since it changes abruptly from a class risk to another not consecutive depending only on the lambda picked at each simulation. In this example, Company D jumps from class 3 to 5 any time the $\lambda$ considered at each simulation is below 0.778. Such phenomenon reveals a weakness of this enterprise.

The last example has suggested us to enrich the analysis by considering also imprecise evaluations on the criteria. In fact, since for innovative projects the risks are mostly due to the uncertainties in the data, we have considered the criteria expressed in terms of intervals. In the case study considered, a few qualitative criteria have been considered precise especially the ones expressed in a binary code. For the other qualitative data, we suppose that the evaluations of considered alternatives on each criterion are integer numbers within an interval. For example, the evaluation of Company A on criterion $g_{(3)}$ can be 3, 4 or 5. For the financial criteria, to be prudential we have lowered their evaluations by 20% (see Table 9).

| Table 9: Evaluation matrix with the criteria expressed in terms of intervals. |
| Company | $g_{(1)}$ | $g_{(2)}$ | $g_{(3)}$ | $g_{(4)}$ | $g_{(5)}$ | $g_{(6)}$ | $g_{(7)}$ | $g_{(8)}$ | $g_{(9)}$ | $g_{(10)}$ |
| A   | 4 | 3 | [3, 5] | [4, 5] | [4, 4] | 0 | 0 | [0.44, 0.55] | [0.05, 0.06] | [0.19, 0.24] | [0.18, 0.22] | [0.59, 0.74] |
| B   | 4 | 5 | [4, 5] | [4, 5] | [1, 3] | 0 | 1 | [0.58, 0.72] | [0.14, 0.17] | [0.02, 0.03] | [0.12, 0.14] | [0.41, 0.51] |
| C   | 5 | 3 | [4, 5] | [2, 4] | [4, 5] | 1 | 1 | [0.14, 0.18] | [0.04, 0.05] | [0.75, 0.94] | [0.3, 0.36] | [0.45, 0.56] |
| D   | 4 | 5 | [3, 5] | [2, 3] | [4, 5] | 1 | 0 | [0.05, 0.06] | [0.11, 0.14] | [0.42, 0.52] | [0.11, 0.13] | [0.21, 0.26] |

The category acceptabilities obtained are shown in Table 10.

| Table 10: Category acceptabilities with the evaluations criteria in terms of intervals |
| Company | Class 1 | Class 2 | Class 3 | Class 4 | Class 5 | Category Result |
| A   | 0% | 0% | 10% | 90% | 0% | $C_4$ |
| B   | 0% | 0% | 10% | 40% | 50% | $C_5$ |
| C   | 0% | 0% | 17% | 50% | 34% | $C_4$ |
| D   | 0% | 0% | 40% | 26% | 35% | $C_3$ |

Let us observe that depending on the decisional point of view of the bank, the credit officers could fix the lowest probability that allows a category to which a company has to be sorted. For example, if $\pi_i^4 > 0.7$ then the company $i$ is assigned to the class $C_4$ (see Table 10). In our case study, this means that only Company A will be sorted to the class $C_4$.

Moreover, the combination of the imprecision on the criteria and the simulation process shows to be a useful risk assessment tool since it reveals some weaknesses of companies C and D.

In fact, while the assignments of companies A and B are unchanged, the assignments of Company C and especially Company D are changed significantly (see Table 10). The uncertainty on the data has lowered the categories of companies C and D comparing with the category results at a group
level (see Table 8(b)). Such results can be linked to the remark on the non-monotonic behavior considered above.

At this point, it could be useful an analysis of the mortality rates of the enterprises of the sectors considered to strengthen or lower the evaluation given by the multicriteria model. At this aim, we have reported in Table 11 the mortality rates for the sectors under consideration over the period 2008-2012 and we have compared them to the ones of all the Italian SMEs.

Table 11: Mortality rates (data from ISTAT)

| Sector   | 2008 | 2009 | 2010 | 2011 | 2012 |
|----------|------|------|------|------|------|
| Company A| 5.2% | 4.9% | 4.9% | 4.9% | 4.8% |
| Company B| 9.1% | 7.5% | 7.8% | 8.1% | 7.5% |
| Company C| 12.8%| 9.6% | 11.4%| 9.9% | 9.2% |
| Company D| 10.8%| 9.6% | 11.4%| 10.7%| 11.3%|
| Italian SMEs | 7.1% | 7.9% | 7.8% | 7.7% | 8.1% |

From a macroeconomic point of view also this analysis reveals a high risk to finance enterprises C and D since the mortality rates of C and D sectors are greater than those at a national level.

Finally, it is still important to emphasize that in the judgmental credit risk model considered, we have never introduced any veto criterion. The introduction of veto criteria is expected to have a considerable impact on the decision procedure. In fact, let us suppose for example to consider the criterion availability of testing and unit pilots ($g_4^4$) as a veto criterion. One implication of the inclusion of this veto criterion is that, when an enterprise doesn’t have a unit pilot (thus receiving a 0 point in the evaluation according to this criterion), the criterion would be against the assignment of such an enterprise to a good risk class. Such enterprise would be assigned to the class $C_1$, even if it has a good evaluation on the majority of criteria. In the case study, for example only the enterprise Company C has a good evaluation on this criterion. As a result, in many real situations, it may be very relevant to impose some veto criteria.

6 Conclusions

Many recent studies have been dedicated to measuring SMEs’ innovation considered as a crucial factor for the development of a national economy (Brandolini and Bugamelli, 2009). To achieve a high level of innovation the main obstacle that the innovative SMEs face is a non-straightforward access to credit. For example in Italy, such asymmetric information is due to the small dimension of most of the innovative SMEs (Bugamelli et al., 2012). To help innovative enterprises, financial institutions could try to reduce such informative asymmetries. Presently, banks assess their credit risk by evaluating the business plan and considering some non-financial information such as the market trend and the quality of the management team. Although financing innovation isn’t an easy task due to the lack of track records of innovative SMEs, we believe that a rating model based upon experts’ judgments could improve it. In financing innovative SMEs, the role of the experts is crucial, since they can help the credit officers in selecting the proper criteria, especially, in detecting their risks.

In this paper, we have presented a multicriteria approach to sort innovative enterprises into risk classes, mainly on the basis of soft information.

Specifically, we describe a possible hierarchical structure of the innovation risks: development, production, market and technological ones. Such risk indicators have been considered together with some financial criteria. The multicriteria approach proposed is ELECTRE-TRI based on an outranking preference relation comparing each innovation to some existing risk profiles. As explained
in the paper, the multidimensional and complex decisional framework of financing innovation is well adapted to the aforementioned multicriteria method.

In fact, the credit officers with the help of the experts could define the risk profiles, the criteria weights, but could also tune some specific parameters such as the cutting level, the preference, indifference and veto thresholds on which the final ratings depend.

Finally, we envisage some possible research lines for the future:

- It could be interesting to detect the most “critical” criteria governing the decision making process. What is meant by the term “critical” here is the smallest change that might occur to a certain criterion in order increase the category acceptability of the better risk class to which each enterprise has been assigned.

- ELECTRE-TRI is a non-compensatory method; maybe it could be useful to consider also other multicriteria models including interaction between criteria (see the Choquet integral preference model among the multicriteria approaches representing interaction between criteria e.g. in Angilella et al., 2004 and its recent extension within a SMAA methodology in Angilella et al., 2012).

- Since the criteria adopted in this paper are hierarchically structured, it could be useful to apply the recent approach of the hierarchal Choquet integral presented in Angilella et al., 2013.

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**References**

E.I. Altman and G. Sabato. Modelling credit risk for SMEs: Evidence from the U.S. market. *Abacus*, 43(3):332–357, 2007.

E.I. Altman, G. Sabato, and N. Wilson. The value of non-financial information in small and medium-sized enterprise risk management. *The Journal of Credit Risk*, 6(2):1–33, 2010.

S. Angilella, S. Greco, F. Lamantia, and B. Matarazzo. Assessing non-additive utility for multicriteria decision aid. *European Journal of Operational Research*, 158(3):734–744, 2004.

S. Angilella, S. Corrente, and S. Greco. SMAA-Choquet: Stochastic multicriteria acceptability analysis for the Choquet integral. In S. Greco et al., editor, *Advances in Computational Intelligence*, volume 300 of *Communications in Computer and Information Science*, pages 248–257. Springer Berlin Heidelberg, 2012.

S. Angilella, S. Corrente, S. Greco, and R. Słowiński. Multiple criteria hierarchy process for the Choquet integral. In R.C. Purshouse et al., editor, *EMO 2013*, volume 7811 of *LNCS*, pages 475–489. Springer Berlin Heidelberg, 2013.

H.V. Auken, G.H. Cánovas, and A.M. Guijarro. Role of information in the debt financing of technology-based firms in Spain. In *The Entrepreneurial Society: How to Fill the Gap Between Knowledge and Innovation*. Edward Elgar Publishing Inc., 2010.
C.A. Bana e Costa and J.C. Vansnick. A theoretical framework for measuring attractiveness by a categorical based evaluation technique (MACBETH). *In Proc. XIth Int. Conf. on Multicriteria Decision Making, 15-24, Coimbra, Portugal, August 1994.*

C.A. Bana e Costa and J.C. Vansnick. Applications of the MACBETH approach in the framework of an additive aggregation model. *Journal of Multi-Criteria Decision Analysis, 6:107–114, 1997.*

C.A. Bana e Costa and J.C. Vansnick. The macbeth approach: Basic ideas, software, and an application. In N. Meskens and M.R. Roubens, editors, *Advances in Decision Analysis*, volume 4 of *Mathematical Modelling: Theory and Applications*, pages 131–157. Kluwer, 1999.

C.A. Bana e Costa, L.A. Barroso, and J.O. Soares. Qualitative modelling of credit scoring: A case study in banking. *European Research Studies, V(1-2):37–51, 2002.*

T. Beck and A. Demirgüç-Kunt. Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance, 30(11):2931 – 2943, 2006.*

T. Beck, A. Demirgüç-Kunt, and M.S. Martínez Pería. Bank financing for SMEs: Evidence across countries and bank ownership types. *Journal of Financial Services Research, 39(1-2):35–54, 2011.*

A.N. Berger and G.F. Udell. *Financial system design: the case for universal banking. Irwin (Richard D), Burr Ridge*, chapter Universal Banking and the Future of Small Business Lending, pages 559 – 627. 1996.

A.N. Berger and G.F. Udell. A more complete conceptual framework for SME finance. *Journal of Banking & Finance, 30(11):2945 – 2966, 2006.*

A.N. Berger, N.H. Miller, M.A. Petersen, R.G. Rajan, and J.C. Stein. Does function follow organizational form? evidence from the lending practices of large and small banks. *Journal of Financial Economics, 76(2):237 – 269, 2005.*

A. Brandolini and M. Bugamelli. Report on trends in the Italian productive system. *Questioni di Economia e Finanza (Occasional Papers) 45, Bank of Italy, Economic Research and International Relations Area, April 2009.*

J.P. Brans and Ph. Vincke. A preference ranking organization method. *Management Science, 31(6): 647–656, 1985.*

J.P. Brans, B. Mareschal, and Ph. Vincke. *Operational Research ’84, chapter PROMETHEE: A new family of outranking methods in multicriterinia analysis, pages 408–421. Elsevier Science Publishers B.V. (North-Holland)*, 1984.

R.J. Brown, S.M. Fazzari, and C.B. Petersen. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance, 54(1):151–185, 2009.*

M. Bugamelli, L. Cannari, F. Lotti, and S. Magri. The innovation gap of Italy’s production system, roots and possible solutions. *Questioni di Economia e Finanza (Occasional Papers) 121, Bank of Italy, Economic Research and International Relations Area, April 2012.*

R. Canales and R. Nanda. A darker side to decentralized banks: Market power and credit rationing in SME lending. *Journal of Financial Economics, 105(2):353 – 366, 2012.*

J.N. Crook, D.B. Edelman, and L.C. Thomas. Recent developments in consumer credit risk assessment. *European Journal of Operational Research, 183(3):1447 – 1465, 2007.*
D. Czarnitzki and H. Hottenrott. R & D investment and financing constraints of small and medium-sized firms. *Small Business Economics*, 36:65–83, 2011.

M. Doumpos and C. Zopounidis. A multicriteria decision support system for bank rating. *Decision Support Systems*, 50(1):55–63, 2010.

M. Doumpos, K. Kosmidou, G. Baourakis, and C. Zopounidis. Credit risk assessment using a multicriteria hierarchical discrimination approach: a comparative analysis. *European Journal of Operational Research*, 138(2):392–412, 2002.

J. Figueira, S. Greco, B. Roy, and R. Slowiński. *Handbook of Multicriteria Analysis*, chapter ELECTRE Methods: main features and recent developments. Springer, New York, 2010.

S. Greco, B. Matarazzo, and R. Slowiński. Comments on: Multicriteria decision systems for financial problems. *TOP*, pages 1–7, 2013.

J. Grunert, L. Norden, and M. Weber. The role of non-financial factors in internal credit ratings. *Journal of Banking & Finance*, 29:509–531, 2005.

E. Jacquet-Lagrèze. An application of the UTA discriminant model for the evaluation of R & D projects. In P. M. Pardalos, Yannis Siskos, and Constantin Zopounidis, editors, *Advances in Multicriteria Analysis*, volume 5 of *Nonconvex Optimization and Its Applications*, pages 203–211. Springer US, 1995.

E. Jacquet-Lagrèze and J. Siskos. Assessing a set of additive utility functions for multicriteria decision-making, the UTA method. *European Journal of Operational Research*, 10(2):151–164, 1982.

R.L. Keeney and H. Raiffa. *Decisions with multiple objectives: Preferences and value tradeoffs*. J. Wiley, New York, 1976.

A. Kleinknecht, K. Van Montfort, and E. Brouwer. The non-trivial choice between innovation indicators. *Economics of Innovation and New Technology*, 11(2):109–121, 2002.

P.R. Kumar and V. Ravi. Bankruptcy prediction in banks and firms via statistical and intelligent techniques: A review. *European Journal of Operational Research*, 180(1):1 – 28, 2007. ISSN 0377-2217.

S. Mazzù. *Il finanziamento dell’innovazione. Strumenti, rischi e modelli di valutazione*. G. Giappichelli, 2008.

D.C. Morais, A.T. de Almeida, and J.R. Figueira. A sorting model for group decision making: A case study of water losses in Brazil. *Group Decision and Negotation*, 2012.

A. Moro and M. Fink. Loan managers’ trust and credit access for SMEs. *Journal of Banking & Finance*, 37(3):927 – 936, 2013.

V. Mousseau. *Advances in Multicriteria Analysis*, *Nonconvex Optimization and its Applications*, volume 5, chapter Eliciting information concerning the relative importance of criteria, pages 17–43. Kluwer Academic Publishers, Dordrecht, 1995.

V. Mousseau, J. Figueira, and J.P. Naux. Using assignment examples to infer weights for ELECTRE-TRI method: Some experimental results. *European Journal of Operational Research*, 130(2):263–275, 2001.
P. Nemery, A. Ishizaka, M. Camargo, and L. Morel. Enriching descriptive information in ranking and sorting problems with visualizations techniques. *Journal of Modelling in Management*, 7(2):130–147, 2012.

B. Roy. Classement et choix en présence de points de vue multiples: La méthode ELECTRE. *Revue Francaise d’Informatique et de Recherche Operationnelle*, 8:57–75, 1968.

B. Roy. *Méthodologie Multicritère d’Aide à la Décision*. Economica, Paris, 1985.

B. Roy. The outranking approach and the foundations of ELECTRE methods. *Theory and Decision*, 31(1):49–73, 1991.

B. Roy. Decision science or decision-aid science? *European Journal of Operational Research*, 66(2):184–203, 1993.

B. Roy and J.R. Figueira. Determining the weights of criteria in the ELECTRE type methods with a revised Simos’ procedure. *European Journal of Operational Research*, 139:317–326, 2002.

B. Roy and V. Mousseau. A theoretical framework for analyzing the notion of relative importance of criteria. *Journal of Multi-criteria Decision Analysis*, 5:145–159, 1996.

D. Shefer and A. Frenkel. R & D, firm size and innovation: an empirical analysis. *Technovation*, 25(1):25 – 32, 2005.

T. Tervonen. JSMAA: open source software for SMAA computations. *International Journal of Systems Science*, pages 1–13, 2012.

T. Tervonen, R. Lahdelma, J. Almeida Dias, J.R. Figueira, and P. Salminen. SMAA-TRI. In I. Linkov, G.A. Kiker, and R.J. Wenning, editors, *Environmental Security in Harbors and Coastal Areas*, NATO Security through Science Series, pages 217–231. Springer Netherlands, 2007.

T. Tervonen, J.R. Figueira, R. Lahdelma, D.A. Juscelino, and P. Salminen. A stochastic method for robustness analysis in sorting problems. *European Journal of Operational Research*, 192(1):236–242, 2009.

C. Tronnberg and S. Hemlin. Lending decision making in banks: A critical incident study of loan officers. *European Management Journal*, 32(2):362 – 372, 2014.

Ph. Vincke. *Multicriteria decision-aid*. Wiley, New York, 1992.

F. Voulgaris, M. Doumpos, and C. Zopounidis. On the evaluation of Greek industrial SME’s performance via multicriteria analysis of financial ratios. *Small Business Economics*, 15(2):127–136, 2000.

W. Yu. *ELECTRE TRI*: Aspects méthodologiques et manuel d’utilisation. Document du LAMSADE No.74, Université Paris-Dauphine, June 1992.

C. Zopounidis and M. Doumpos. Multicriteria classification and sorting methods: A literature review. *European Journal of Operational Research*, 138:229–246, 2002.

C. Zopounidis and M. Doumpos. A multicriteria outranking modeling approach for credit rating. *Decision Sciences*, 42(3):721–742, 2011.
Table 12: Scenario analysis

(a) Company A

| Year   | Initial cash flows | NPV (7.93%) |
|--------|-------------------|-------------|
| Cash-flow (£) | -43,614.00       | 140,257.64  |
| year 1 | 69,616.91         | 118,470.63  |
| year 2 | 9,178.96          | 87,168.96   |
| year 3 | 118,470.63        | 140,257.64  |
| year 4 | 140,257.64        | 140,257.64  |

Cash flows lowered by 20%:

| Year   | Cash flows lowered by 20% | NPV (7.93%) |
|--------|---------------------------|-------------|
| Cash-flow (£) | -52,240.80       | 120,523.28  |
| year 1 | 62,156.00          | 118,470.63  |
| year 2 | 9,178.96           | 77,395.69   |
| year 3 | 118,470.63         | 140,257.64  |
| year 4 | 140,257.64         | 140,257.64  |

Cash flows lowered by 40%:

| Year   | Cash flows lowered by 40% | NPV (7.93%) |
|--------|---------------------------|-------------|
| Cash-flow (£) | -60,947.60        | 96,154.86   |
| year 1 | 81,832.00           | 118,470.63  |
| year 2 | 9,178.96            | 77,395.69   |
| year 3 | 118,470.63          | 140,257.64  |
| year 4 | 140,257.64          | 140,257.64  |

(b) Company B

| Year   | Initial cash-flows | NPV (7.93%) |
|--------|-------------------|-------------|
| Cash-flow (£) | - 8,715.00        | 57,472.00   |
| year 1 | -15,528.00        | 45,977.60   |
| year 2 | 52,196.00         | 73,362.71   |
| year 3 | 58,422.00         | 73,362.71   |
| year 4 | 57,472.00         | 73,362.71   |
| year 5 | 102,405.74        | 102,405.74  |

Cash flows lowered by 20%:

| Year   | Cash flows lowered by 20% | NPV (7.93%) |
|--------|---------------------------|-------------|
| Cash-flow (£) | -10,458.00       | 73,362.71   |
| year 1 | -18,633.60          | 45,977.60   |
| year 2 | 41,756.80           | 73,362.71   |
| year 3 | 46,737.60           | 73,362.71   |
| year 4 | 45,977.60           | 73,362.71   |
| year 5 | 73,362.71           | 73,362.71   |

Cash flows lowered by 40%:

| Year   | Cash flows lowered by 40% | NPV (7.93%) |
|--------|---------------------------|-------------|
| Cash-flow (£) | -12,201.00       | 44,319.08   |
| year 1 | -21,739.20          | 34,483.20   |
| year 2 | 31,317.60           | 44,319.08   |
| year 3 | 35,053.20           | 44,319.08   |
| year 4 | 34,483.20           | 44,319.08   |
| year 5 | 44,319.08           | 44,319.08   |

(c) Company C

| Year   | Initial cash flows | NPV (7.93%) |
|--------|-------------------|-------------|
| Cash-flow (£) | -211,100.00      | 1,032,614.23|
| year 1 | 126,643.19        | 160,260.61  |
| year 2 | 196,643.19        | 246,882.41  |
| year 3 | 246,882.41        | 317,044.14  |
| year 4 | 317,044.14        | 387,205.88  |
| year 5 | 387,205.88        | 458,367.62  |
| year 6 | 458,367.62        | 539,529.38  |

Cash flows lowered by 20%:

| Year   | Cash flows lowered by 20% | NPV (7.93%) |
|--------|---------------------------|-------------|
| Cash-flow (£) | -253,320.00      | 642,152.30  |
| year 1 | -101,234.55          | 246,882.41  |
| year 2 | 156,827.48           | 246,882.41  |
| year 3 | 187,010.95           | 246,882.41  |
| year 4 | 351,154.01           | 317,044.14  |
| year 5 | 454,671.33           | 387,205.88  |
| year 6 | 642,152.30           | 458,367.62  |

Cash flows lowered by 40%:

| Year   | Cash flows lowered by 40% | NPV (7.93%) |
|--------|---------------------------|-------------|
| Cash-flow (£) | -295,440.09      | 383,819.35  |
| year 1 | -75,925.91           | 196,643.19  |
| year 2 | 117,620.61           | 246,882.41  |
| year 3 | 190,268.21           | 317,044.14  |
| year 4 | 263,356.51           | 387,205.88  |
| year 5 | 383,819.35           | 458,367.62  |

(d) Company D

| Year   | Initial cash-flows | NPV (7.93%) |
|--------|-------------------|-------------|
| Cash-flow (£) | -62,272.07       | 988,208.95  |
| year 1 | 204,057.11        | 1,094,740.87|
| year 2 | 1,094,740.87      | 1,094,740.87|
| year 3 | 988,208.95        | 988,208.95  |

Cash flows lowered by 20%:

| Year   | Cash flows lowered by 20% | NPV (7.93%) |
|--------|---------------------------|-------------|
| Cash-flow (£) | -74,129.48       | 767,488.48  |
| year 1 | 160,219.38          | 875,192.09  |
| year 2 | 875,192.09          | 767,488.48  |
| year 3 | 767,488.48          | 767,488.48  |

Cash flows lowered by 40%:

| Year   | Cash flows lowered by 40% | NPV (7.93%) |
|--------|---------------------------|-------------|
| Cash-flow (£) | -87,180.89       | 646,768.00  |
| year 1 | 122,154.28          | 646,768.00  |
| year 2 | 636,814.32          | 646,768.00  |
| year 3 | 646,768.00          | 646,768.00  |
Table 13: Comparisons with the sector.

(a) Company A

| Intangible Asset/Fixed Asset | R&D/Sales | ROA  | Short term debt/Equity | Cash/Total Asset |
|-----------------------------|-----------|------|------------------------|------------------|
| Company A                   | 0.55      | 0.24 | 0.18                   | 0.73             |
| min                         | 0.00      | 0.00 | 0.14                   | 0.02             |
| Quartile 25                 | 0.02      | -    | -0.04                  | 0.14             |
| Quartile 50                 | 0.01      | -    | 0.01                   | 1.07             |
| Quartile 75                 | 0.20      | -    | 0.05                   | 0.18             |
| max                         | 0.20      | -    | 0.05                   | 0.18             |

(b) Company B

| Intangible Asset/Fixed Asset | R&D/Sales | ROA  | Short term debt/Equity | Cash/Total Asset |
|-----------------------------|-----------|------|------------------------|------------------|
| Company B                   | 0.72      | 0.17 | 0.72                   | 0.51             |
| min                         | 0.00      | -    | 0.01                   | 0.00             |
| Quartile 25                 | 0.00      | -    | 0.01                   | 0.02             |
| Quartile 50                 | 0.17      | -    | 0.03                   | 0.00             |
| Quartile 75                 | 1.34      | -    | 0.09                   | 0.18             |
| max                         | 1.34      | -    | 0.09                   | 0.18             |

(c) Company C

| Intangible Asset/Fixed Asset | R&D/Sales | ROA  | Short term debt/Equity | Cash/Total Asset |
|-----------------------------|-----------|------|------------------------|------------------|
| Company C                   | 0.18      | 0.05 | 0.35                   | 0.55             |
| min                         | 0.00      | -    | 0.01                   | 0.01             |
| Quartile 25                 | 0.00      | -    | 0.01                   | 0.01             |
| Quartile 50                 | 0.09      | -    | 0.04                   | 0.06             |
| Quartile 75                 | 0.43      | -    | 0.10                   | 0.16             |
| max                         | 0.43      | -    | 0.10                   | 0.16             |

(d) Company D

| Intangible Asset/Fixed Asset | R&D/Sales | ROA  | Short term debt/Equity | Cash/Total Asset |
|-----------------------------|-----------|------|------------------------|------------------|
| Company D                   | 0.06      | 0.14 | 0.34                   | 0.56             |
| min                         | 0.00      | -    | 0.04                   | 0.01             |
| Quartile 25                 | 0.00      | -    | 0.04                   | 0.01             |
| Quartile 50                 | 0.07      | -    | 0.06                   | 0.00             |
| Quartile 75                 | 0.91      | -    | 0.04                   | 0.14             |
| max                         | 0.91      | -    | 0.04                   | 0.21             |

Appendix B

To assess the criteria weights within a Simos’ procedure, the following variables are defined:

- \( z \) is the ratio expressing how many times the last criterion is more important than the first one in the ranking;
- \( e_r' \) is the number of white cards between the rank \( r \) and \( r + 1 \);
- \( e_r = e_r' + 1 \);
- \( u = \frac{z-1}{e} \);
- \( e = \sum_{r=1}^{n-1} e_r \).

The non normalized weight \( k(r) \) is computed by:

\[
k(r) = 1 + u(e_0 + \cdots + e_{r-1}),
\]

with \( e_0 = 0 \).

Let \( k'_i = k(r) \) be the weight relative to the criterion \( i \) and let \( K' = \sum_{i=1}^{n} k'_i \) the sum of the non-normalized weights. The normalized weight \( k^*_i \) is computed by:

\[
k^*_i = \frac{1}{K'} k'_i.
\]
Within the Simos’ procedure, the preference information expressed by the DM1 is reported in Table 14(a), the normalized weights are those displayed in Table 14(b).

### Table 14: Simos’ method

(a) DM1’s set of weights with $z = 8.$

| Rank $r$ | Criteria in the rank $r$ | n. of white cards $e_r$ | Non-normalized weights $k(r)$ | Total |
|----------|---------------------------|--------------------------|-------------------------------|-------|
| 1        | $\{g_1^1, g_1^2\}$       | 0                        | 1                             | 2     |
| 2        | $\{g_5^8, g_5^9\}$        | 0                        | 1                             | 1.63  |
| 3        | $\{g_4^3, g_5^3\}$        | 0                        | 1                             | 2.27  |
| 4        | $\{g_5^{10}, g_5^{11}, g_5^{12}\}$ | 5                        | 6                             | 2.90  |
| 5        | $\{g_2^3\}$              | 0                        | 1                             | 6.72  |
| 6        | $\{g_4^7\}$              | 0                        | 1                             | 7.36  |
| 7        | $\{g_4^6\}$              |                          | 8                             | 8     |
| Total    |                           | e                        | 11                            | $K'$  |

(b) Normalized weights for the DM1.

| $k_i^*$ | $g_1(1)$ | $g_2(2)$ | $g_3(3)$ | $g_4(4)$ | $g_5(5)$ | $g_6(6)$ | $g_7(7)$ | $g_8(8)$ | $g_9(9)$ | $g_{10}(10)$ | $g_{11}(11)$ | $g_{12}(12)$ |
|---------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|         | 0.0250   | 0.0250   | 0.1650   | 0.0560   | 0.0560   | 0.1960   | 0.1810   | 0.0400   | 0.0400   | 0.0720   | 0.0720   | 0.0720   |