Chapter 6
Other Applications of Multicriteria Analysis in Finance

Abstract This chapter illustrates the contributions of MCDA in other areas of financial decision making. First, the investment appraisal process is considered followed by country risk analysis. For the latter, an illustrative application is presented demonstrating preference disaggregation methods that can be used to construct country risk classification models.

Keywords Investment appraisal · Project selection · Country risk analysis

6.1 Investment Appraisal

Decisions on the choice of investment projects often have a strategic character as they span over a large time period and they require considerable resources. The investment decision process consists of four main stages: perception, formulation, evaluation and choice. The financial theory is mostly involved with the evaluation and choice stages, through the introduction of investment appraisal criteria such as the net present value, the internal rate of return, and the payback method. Such criteria are aggregated through empirical approaches resulting to a ranking of a set of investment projects on the basis of their attractiveness or to an acceptance/rejection decision in the case of a single project.

However, there are a number of issues with the above process. First, the analysis is restricted to the evaluation of future cash flows on the basis of a predefined discount rate. Secondly, there is no formal framework for analyzing the discrepancies in the results of different investment appraisal criteria. In a realistic setting, the investment analysis is much more involved than a simple discounting of future financial outcomes. Furthermore, the high uncertainties involved with the outcomes of an investment project cannot always be adequately described in probabilistic terms, especially in cases of strategic investments for which similar past instances or historical data are not available.

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Instead, a comprehensive investment appraisal process requires the careful consideration of possible options (investment projects), the specification of the goals and objectives of the investments, the identification of their consequences and risks, as well as the formulation of the evaluation results. The multicriteria paradigm introduces such a holistic view of the investment selection process, supporting all of its stages. Montibeller et al. [180] analyzed the contributions of MCDA in the problem structuring phase, in the context of project portfolio selection. Concerning the stages of evaluation and choice, MCDA offers a methodological framework much more realistic than the one based solely on financial criteria, which make assumptions that are often not met in practice. For instance, Götze et al. [103] note that investment appraisal based on the net present value, assumes among others that:

1. a single performance measure is adequate,
2. the economic life of the investment is known,
3. the investment appraisal process is separated from other relevant decisions regarding the financing of the project and its operation,
4. the cash flows are known.

In fact, the financial outcomes of the project and the associated risks depend on a number of factors, which are often difficult to quantify. For instance one can mention the strategic benefits of the investment, its relation to the organization strategy of the firm, technical aspects of the investment, operational risk factors related to the implementation of the investment, regulatory and legal issues, etc. Recently new trends have also emerged with regard to socially responsible investments, thus adding ethical, social, and environmental criteria in the analysis.

The multidimensional nature of the investment appraisal process is further highlighted by the multiple objectives that managers seek to achieve through the implementation of an investment project. Bhaskar and McNamee [26] presented empirical results from large companies from the United Kingdom, showing that 96 % of the companies consider more than one objective during the investment selection process (with the most common number of objectives being eight). In most cases, profitability was found to be given top priority, followed by company growth, risk, liquidity, flexibility, etc.

In a venture capital investment context, empirical survey studies have presented extensive empirical results from survey studies conducted among US, UK, and European venture capital firms, in order to identify the criteria that they consider in their investment process [62, 109, 159, 184]. The results demonstrate that such investment decisions are driven by a diverse set of qualitative and quantitative factors, involving among others:

- the qualities and experience of the management team of the firms,
- the experience and personality of the entrepreneurs,
- product-market criteria,
- the financial characteristics of the investments,
- the lending guidelines followed by the venture capital firms, etc.

The aggregation of such a diverse set of decision criteria in an ad-hoc manner, without a solid, structured, and sound framework underlying the characteristics of the evaluation process can easily lead to flawed and unexpected results. For instance, Keeney [138] analyzes 12 common mistakes in making value trade-offs, which are also relevant in other evaluation contexts. Among the most generally applicable ones, we can mention the following:

- not understanding the decision context,
- not having measures for consequences (i.e., criteria),
- using inadequate measures,
- not knowing what the measures represent,
- replacing fundamental objectives with alternative proxies,
- focusing on calculating "correct" trade-offs,
- using screening criteria imposing value judgments,
- failure to use consistency checks.

The MCDA paradigm provides investors and managers with a systematic approach to handle such issues, thus enabling the consideration of the investment appraisal process in a realistic and flexible multicriteria context. Among others, MCDA techniques, which are applicable in investment appraisal are involved with issues such as:

1. facilitating the managers in specifying a solid and transparent structure of the investment selection process,
2. analyzing the trade-offs among the investment selection criteria and measuring their relative importance,
3. aggregating multiple appraisal measures of diverse nature (qualitative, quantitative, deterministic, stochastic, fuzzy, etc.) into global investment selection indices,
4. exploring the uncertainties involved in the selection process, through systematic sensitivity and robustness analyses.

Table 6.1 reports some recent studies using MCDA approaches for investment appraisal in different contexts.

6.2 Country Risk Analysis

6.2.1 The Context of Country Risk Assessment

The oil crises of the 1970s and the resulting worldwide economic turmoil were the first post-war events that highlighted the importance of a global risk factor for sustainable socio-economic development as well as for the operation of firms worldwide. More recent events, such as the crises in Southeast Asia (1997), South America (2002), as well as the global credit crisis of 2007–2008 and the subsequent European sovereign debt crisis are clear examples that demonstrate the relevance of country risk for financial decision making.

Table 6.1 Some recent studies on investment appraisal under multiple criteria

Information and communication technologies [5]
Army modernization [41]
Transport [55]
International project portfolios [112]
Cash flow modeling [132]
Capital budgeting under fuzziness and uncertainty [149]
Transport [158]
Energy systems [192]
Shipping [206]
Wind farm site selection [108]
Product design [253]

Country risk has many facets, which arise from the different perspectives that financial decision makers view the economic and financial development of a country and the difficulties that it faces. From an economic perspective, country risk can be defined as the probability that a country will fail to generate enough foreign exchange to pay its obligations toward its foreign creditors [50]. This economic point of view, however, is focused on the capacity of a country to service its debt. Socio-economic factors are also highly relevant, as they represent the willingness of a country to service its debt. In that regard, country risk can be defined in broader context as the potential economic and financial losses due to the difficulties raised from the macro-economic and/or political environment of a country [38]. Such a definition covers not only the losses for the creditors of a country (financial institutions, organizations, other countries, etc.), but also losses that any corporate entity and institutional or private investor may experience for investments undertaken in a country. For instance, Claude et al. [45] analyzed the relevance and applications of country risk analysis to the portfolio management process, including equity and fixed income portfolios. On the other hand, from the perspective of corporate financial investments, macro and micro risks can be further identified [115, 243]. Macro (sociopolitical) risks arise from dramatic events such as wars, sectarian conflicts, revolutions, etc., as well as less dramatic events such as the country-wide imposition of price controls, tax increases or surcharges, etc. Micro risks, on the other hand, concern circumstances involving industry, firm or project-specific cancellation of import and export licenses, discriminatory taxes, etc.

As an example of the issues involved in country risk analysis, one may consider the diversity of the factors examined by the three main credit rating agencies (Moody's, Standard and Poor's, Fitch), which include [94]:

- Macro-economic conditions and growth factors related to the scale of the economy in a country, its competitiveness, its ability to achieve sustainable growth, and the effectiveness of monetary policies.

- Public finance factors describing the ability of a government's revenue-raising efficiency, its effectiveness in handling expenditures, managing its assets, and obtaining foreign currency.
- Debt factors related to the level, structure, and dynamics of public debt.
- Financial sector attributes that focus on the strength of a country's financial sector, its effectiveness, and the quality of its supervision.
- External finances related to the balance of payments, foreign exchange reserves adequacy, and the structure of the current account.
- Exchange rate regimes and their compatibility to a country's monetary goals.
- Political factors, including geopolitical risk, policy transparency, international relations, public security, as well as the stability and legitimacy of political regime in a country.
- Structural and institutional factors covering issues such as corruption, transparency, institutional independence, the efficiency of the public sector, the strength of the business environment, and the level of innovation.
- Other factors related to the labor market, the openness of the economy, as well as risks from natural disasters.

The first attempts to establish country risk assessments were mainly based on checklist systems focused on economic variables. However, this approach has been proven to be insufficient mainly due to its inability to establish a sound methodological framework for the selection and weighting of the variables. To address this issue, several statistical techniques have been used, mainly oriented towards building models for analyzing and predicting debt reschedulings (for an overview, see [144]) and the country risk ratings issued by rating agencies and international organizations. An overview of international practices in country risk ratings and their primary dimensions can be found in Claude at el. [45], whereas a recent report by the International Monetary Fund focuses on the ratings issued by the three major rating agencies (Standard and Poor's, Moody's, Fitch) and analyzes their role in the recent global crisis as well as their accuracy and information value [94] (Chap. 3).

6.2.2 *Multicriteria Approaches to Country Risk Analysis*

The MCDA methodologies have been used for country risk assessment to develop models that rank or classify countries into risk groups. Tang and Espinal [237] developed a multiattribute model to assess country risk, both on a short and medium-long term basis. The model considered 14 risk criteria related to the countries' external repayment capability, their liquidity, per capital income and population growth, as well as purchasing power risk. The selection and weighting of the criteria was based on the Delphi method. The model was applied to a sample of 30 developed and developing countries. The results showed that the most significant country risk indicator both for short and medium-long terms was the external repayment capability of a country. The ranking of the countries according to the multicriteria model was found to be consistent with the evaluations of two international banks.

Oral et al. [189] proposed a generalized logistic regression model to assess country risk. The parameters of the model were estimated through a mathematical programming formulation controlling for the geopolitical economic characteristics of the countries. The model reproduced the country risk rating scores of Institutional Investor and it was applied to a sample of 70 countries for the years 1982 and 1987. A comparison with logistic regression and regression trees indicated the superiority of the new method over statistical models. Regarding the importance of country risk indicators, the three models provided similar results, highlighting the importance of indicators such as debt/exports, gross national product (GNP) per capita, and investments/GNP.

Cosset et al. [50] applied a preference disaggregation methodology for the development of a country risk ranking model, based on the UTASTAR multicriteria method [221]. Using a sample of 22 reference countries, an additive value model was interactively developed, which consistently represented the preferences of a decision maker. The most important determinants of sovereign creditworthiness were found to be the GNP per capita ratio, propensity to invest, as well as the current account balance to GNP ratio.

6.2.2.1 An Illustration for Country Risk Classification

Except for the above studies that focused on multicriteria models for ranking countries, classification approaches have also been used. Multicriteria classification techniques are particularly well-suited to country risk assessment as they enable the construction of risk rating models that assign countries into predefined risk categories, in accordance with rating systems commonly used by investors, policy makers, and financial risk analysts.

Following such an approach Doumpos et al. [66] used the MHDIS method (Multi-group Hierarchical DIScrimination [266]) for the construction of a classification model. Similarly to the UTADIS method (see Sect. 4.4), the MHDIS method also employs a value function modeling approach. However, often alternatives (e.g., countries) belonging into different performance categories may have very different characteristics, thus making a single scoring model unable to fully describe the data and discriminate the categories. To address this issue, the MHDIS method leads to the construction of multiple value functions. For instance, assume a country risk classification problem in which countries are grouped in N ordered risk categories $C_1, \ldots, C_N$, defined such that C_1 is the low risk group and C_N the high risk one. The modeling approach of the MHDIS method is based on $N-1$ pairs of value functions $\{V_\ell(\mathbf{x}), V_{\sim\ell}(\mathbf{x})\}$, $\ell = 1, \ldots, N-1$, where $V_\ell(\mathbf{x})$ is the value function corresponding to risk category C_ℓ and $V_{\sim\ell}(\mathbf{x})$ describes countries in higher risk classes $C_{\ell+1}, \ldots, C_N$. The two evaluation functions are parameterized by different trade-offs and marginal value functions, each representing the characteristics of countries in class C_ℓ versus countries in categories $C_{\ell+1}, \ldots, C_N$. Under this setting a country i is classified to the risk category with the lowest index ℓ^*, such that $V_{\ell^*}(\mathbf{x}_i) \geq V_{\sim\ell^*}(\mathbf{x}_i)$.

The value functions have a piecewise linear additive form similar to the one described in Sect. 4.4. They are constructed using a preference disaggregation approach that combines three optimization models. The first model is a linear program that minimizes the weighted sum of all absolute errors for the countries in a reference (training) sample, on the basis of the above classification rule:

$$\begin{array}{lll} \min & \sum_{\ell=1}^{N} \frac{1}{M_\ell} \sum_{\mathbf{x}_i \in C_\ell} (\varepsilon_{\ell i}^{+} + \varepsilon_{\ell i}^{-}) & \\ \text{s.t.} & V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) + \varepsilon_{\ell i}^{+} \geq \delta, & \forall\, \mathbf{x}_i \in C_\ell \\ & V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) - \varepsilon_{\ell i}^{-} \leq -\delta, & \forall\, \mathbf{x}_i \in \{C_{\ell+1}, \ldots, C_N\} \\ & \varepsilon_{\ell i}^{+}, \varepsilon_{\ell i}^{-} \geq 0 & \end{array}$$

where δ is a user-defined small positive constant. At a second stage, the classification results from the model derived from the above formulation, are calibrated to reduce the number of misclassifications. In particular, let *MIS* denote the countries misclassified according to the set of additive value functions resulting from the above linear program. The objective of the second stage is to minimize the number of these cases, while retaining all the correct assignments for the other countries (set *COR* of correctly classified countries). This is achieved through the following mixed-integer program:

$$\begin{array}{lll} \min & \sum_{\ell=1}^{N} \frac{1}{M_\ell} \sum_{\mathbf{x}_i \in C_\ell \cap MIS} (y_{\ell i}^{+} + y_{\ell i}^{-}) & \\ \text{s.t.} & V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) \geq \delta, & \forall\, \mathbf{x}_j \in C_\ell \cap COR \\ & V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) \leq -\delta, & \forall\, \mathbf{x}_i \in \{C_{\ell+1}, \ldots, C_N\} \cap COR \\ & V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) + y_{\ell i}^{+} \geq \delta & \forall\, \mathbf{x}_i \in C_\ell \cap MIS \\ & V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) + y_{\ell i}^{-} \leq -\delta, & \forall\, \mathbf{x}_i \in \{C_{\ell+1}, \ldots, C_N\} \cap MIS \\ & y_{\ell i}^{+}, y_{\ell i}^{-} \in \{0, 1\} & \end{array}$$

The first two constraints ensure that all correct classifications achieved at the first stage are retained, whereas the following two constraints are only used for misclassified countries. The binary error variables y^+ and y^- indicate whether a country is misclassified or not (in the former case they equal one, otherwise they are zero).

The result of the above mixed-integer formulation provides the best discrimination of the countries in the risk categories, in term of the number of misclassifications. The last stage of the model fitting process involves a final calibration in order to achieve robust results. For a country i correctly classified in risk category C_ℓ, the pair of value functions $\{V_\ell(\mathbf{x}), V_{\sim\ell}(\mathbf{x})\}$ provides a robust result if the difference $V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i)$ is maximized. Similarly, the pair of value functions $\{V_\ell(\mathbf{x}), V_{\sim\ell}(\mathbf{x})\}$ provides a robust result for a country i correctly classified in risk categories $\{C_{\ell+1}, \ldots, C_N\}$ if the difference $V_{\sim\ell}(\mathbf{x}_i) - V_\ell(\mathbf{x}_i)$ is maximized. In that regard, denoting by COR' and MIS' the set of countries classified, respectively correctly and incorrectly, by the value functions developed through the above mixed-integer programming model, the last stage involves the solution of the following linear program:

$$
\begin{array}{lll}
\max & d & \\
\text{s.t.} & V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) - d \geq 0, & \forall\, \mathbf{x}_i \in C_\ell \cap COR' \\
& V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) + d \leq 0, & \forall\, \mathbf{x}_i \in \{C_{\ell+1}, \ldots, C_N\} \cap COR' \\
& V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) \leq 0 & \forall\, \mathbf{x}_i \in C_\ell \cap MIS' \\
& V_\ell(\mathbf{x}_i) - V_{\sim\ell}(\mathbf{x}_i) \geq 0, & \forall\, \mathbf{x}_i \in \{C_{\ell+1}, \ldots, C_N\} > \cap\, MIS' \\
& d \geq 0 &
\end{array}
$$

The first pair of constraints involve only the correctly classified countries. In these constraints, d represents the minimum absolute difference between the global values of each country according to the two value functions, which must be maximized in order to ensure that the obtained results are robust. On the other hand, the second pair of constraints involves the misclassified countries, and it is used to ensure that they will be retained as misclassified. The set of value functions resulting from the linear program can then be employed to classify any country outside the reference sample.

Following this multicriteria approach, Doumpos et al. [66] used a sample of 161 countries over the period 1996–2000. The countries were classified into four groups according to their income classification as defined by the World Bank:

1. High-income economies (class C_1), including 31 countries.
2. Upper-middle income economies (class C_2), including 30 countries.
3. Lower-middle income economies (class C_3), including 44 countries.
4. Low-income economies (class C_4), including 56 countries.

It should be noted, however, that such a classification is only a rough proxy of country risk, as it is focused on the countries' wealth and does not explicitly consider their economic ability to service their debt, or other socio-economic factors that contribute to country risk as explained earlier.

With this limitation in mind, the evaluation of the countries was performed through 12 country risk indicators selected on the basis of the literature on country risk assessment, and their discriminating power in the context of the specific data. The selected indicators and their trade-offs as estimated through the MHDIS method are reported in Table 6.2. The differences in the obtained results are indicative of the diverse characteristics of the four performance categories of countries in the sample. For instance, countries in the high-income group (function V_1) are characterized by high current account balance, high investments (foreign direct investments and capital formation), and low debt service payments.

Given that the countries are classified in four categories, the classification model consists of three pairs of additive value functions, according to which a country i is classified as follows:

$$
\begin{aligned}
&\text{If } V_1(\mathbf{x}_i) > V_{\sim 1}(\mathbf{x}_i), \text{ then } \mathbf{x}_i \in C_1 \\
&\quad \text{else if } V_2(\mathbf{x}_i) > V_{\sim 2}(\mathbf{x}_i), \text{ then } \mathbf{x}_i \in C_2 \\
&\quad\quad \text{else if } V_3(\mathbf{x}_i) > V_{\sim 3}(\mathbf{x}_i), \text{ then } \mathbf{x}_i \in C_3 \\
&\quad\quad\quad \text{else } \mathbf{x}_i \in C_4
\end{aligned}
$$

Table 6.2 Trade-offs of the country risk indicators in the the MHDIS classification model (in %)

Criteria	V_1	$V_{\sim 1}$	V_2	$V_{\sim 2}$	V_3	$V_{\sim 3}$
Current account balance/GDP	16.55	0.78	6.57	28.06	22.36	2.19
Exports of goods and services/GDP	0.80	0.80	0.65	0.65	11.28	8.11
Foreign direct investment/GDP	10.88	0.73	0.59	9.69	0.76	3.11
Gross capital formation/GDP	17.44	0.79	12.58	0.64	3.49	0.50
Inflation	4.21	13.06	2.54	5.66	5.74	0.51
Infant mortality rate	0.77	47.95	26.25	19.84	11.33	20.49
Short-term debt/Total external debt	8.74	0.61	0.61	0.61	0.49	0.49
Total debt service/Exports of goods and services	15.38	2.67	7.75	1.79	0.49	11.71
Total debt service/Gross international reserves	0.60	0.60	6.93	0.60	12.03	0.49
Net domestic credit/GDP	6.60	24.20	33.90	4.29	6.99	29.10
Total external debt/GDP	0.42	6.73	1.20	27.80	16.12	16.21
Total debt service/Gross international reserves	17.61	1.09	0.43	0.38	8.91	7.10

Table 6.3 Classification accuracies (in %)

	2000	1999	1998	1997	1996
MHDIS	94.25	83.67	83.43	81.81	81.52
UTADIS	83.96	81.43	79.76	80.57	79.23
Rough sets	100.00	83.37	74.48	77.72	73.80
Neural networks	92.64	84.32	80.53	79.09	74.79
Discriminant analysis	77.33	76.46	73.93	76.47	76.69
Ordinal logistic regression	72.39	76.17	69.19	67.41	66.58

Table 6.3 presents the overall classification accuracy results for the MHDIS method as well as for UTADIS, and four other popular machine learning and statistical techniques (rough sets, neural networks, discriminant analysis, ordinal logistic regression). The 2,000 data were used for fitting the models (i.e., training data), whereas the previous years were used for back-testing the models in order to assess their discriminating power. The results show that the two MCDA methods provide the best results in this back-testing comparison. The model developed with the MHDIS method has an accuracy rate consistently higher than 80 % in all years. The models constructed with rough sets and neural networks outperform the two statistical methods, but their performance is not robust over time. Even though these models perform exceptionally well in the training data for year 2000, their performance in the back-tests decreases considerably reaching 73–74 % in 1996.