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FOREIGN DIRECT INVESTMENT PERFORMANCE DRIVERS AT THE COUNTRY LEVEL: A ROBUST COMPROMISE MULTI-CRITERIA DECISION-MAKING APPROACH

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Abstract. This paper focuses on the performance drivers of Foreign Direct Investment (FDI) at the country level, exploring the socio-demographic specifics of donor and receiver countries. To this end, a novel Robust Compromise (RoCo) Multi-Criteria Decision-Making (MCDM) model is proposed using non-linear programming solved by genetic algorithms. The model builds upon established traditional models for alternative ranking and criteria weighting. Subsequently, a stochastic robust regression is performed, building upon previously computed bootstrapped Tobit, Simplex, and Beta regressions to handle performance scores ranging between 0 and 1. The goal is to test FDI performance against a set of contextual variables. The findings suggest that the performance of FDI is relatively low, and relevant improvements should be made. Our second stage analysis reports that higher GDP per capita and good social welfare, including lower infant mortality and higher life expectancy, contribute to the improvement in FDI performance. Furthermore, it is found that a large percentage of women in the total population, wealth concentration in the destination country, as well as the degree of urbanization, are helpful to improve FDI performance. Finally, we find that FDI performance is mainly concentrated on industries that are high-tech and high value-added.

Keywords: multiple criteria analysis, FDI, robust analysis, social welfare, economic development, socio-demographic drivers.

JEL Classification: F21, F23, C67, C81.

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1. Introduction

Foreign direct investment (FDI) is thought to be a positive driver of growth (Cuadros et al., 2004). Engaging in FDI can create an environment that enhances the competitive conditions between domestic manufacturers and their international counterparts, which is expected to provide an incentive for domestic industries to optimize the allocation of resources and further improve their efficiency and productivity (Chen et al., 1995; Fernandes & Paunov, 2012). On a more micro-level, the spillover effect derived from FDI helps improve access to finance, enhance product quality, and contribute to the growth of small local suppliers (Dries & Swinnen, 2004). On a macro-level, FDI increases the flow of knowledge spillovers from one country to another (Branstetter, 2006).

Given the importance of FDI as discussed previously, research studies have attempted to investigate its determinants (Ly et al., 2018; Contractor et al., 2020; Paul & Feliciano-Cestero, 2021). While examining the determinants of FDI can guide relevant policymaking, a more fundamental and important question is how to provide more incentives for countries or companies to engage in FDI. In other words, companies or countries would be keen to look at the performance of their FDI activities. Higher performance would induce companies or countries to further engage in these activities, whereas relatively lower performance is supposed to reduce the volumes of FDI activities. Although efforts have been made to evaluate the performance of FDI, most of them used qualitative research methods or relevant accounting indicators. No attempt has been made yet to integrate the multi-criteria decision-making (MCDM) method into the performance evaluation of FDI. The employment of this methodology would not only fill the gap in the literature in international business and FDI but also provide more accurate results, through which more concise policies can be made. Despite FDI has been widely researched, studies on the socio-demographic drivers of FDI remain scant. As far as we know, none of the previous studies to date address the issue regarding the impacts of relevant contextual variables from both donor and receiver countries.

Despite the current developments in FDI, MCDM is a growing field of study, and various approaches are continually being developed and combined to provide a fundamental basis for weighting criteria for ranking alternatives with underlying epistemic uncertainty and measuring performance (Tan et al., 2021; Wanke et al., 2023a). Therefore, this paper fills in the literature gaps by proposing a Robust Compromise (RoCo) MCDM model based on non-linear programming and building upon the findings derived from various other appraoches with regard to alternative rankings and criteria weighting.

Another characteristic of this study is related to the calculation of the weights of the MCDM model and the unbiased criteria using the minimization of the covariance matrix. By incorporating various sources of information to evaluate FDI performance, the utilization of minimal covariance in determining MCDM weights ensures that any unaccounted epistemic uncertainty will not affect each socio-demographic criterion's relative importance. This approach guarantees that performance estimates, derived from a compromise solution that combines different methods and their respective assumptions, remain reliable and robust.

Precisely, as regards alternative ranking: COmplex PRoportional ASsessment (COPRAS), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). On the other hand, as criteria weighting: Step-wise Weight Assessment Ratio Analysis (SWARA) and Analytic Hierarchy Process (AHP). The previous literature mainly focused on using relevant accounting/ratio indicators to measure FDI performance, which, compared to the innovative method we propose in the current study, lacks accuracy and robustness.

We also noticed that some previous studies used stochastic frontier analysis or input distance function. The parametric analysis is affected by the curse of dimensionality, which may yield performance scores biased towards one (Antunes et al., 2023a). The building of MCDM models would be able to help alleviate the issue. In addition, we further contribute to the original MCDM models by proposing a compromise solution, through which the issue of epistemic uncertainty is considered in performance evaluation. In other words, our proposed innovative approach can generate the most robust results on FDI performance.

We propose an MCDM model to measure FDI performance at the country level based on the following theoretical frameworks: 1) institutional theory, which argues that firms and investors are influenced by the institutional environment in different countries, including regulations, laws, and social norms. From this perspective, the quality of the institutional environment can be indicated by the incentives offered to investors; 2) resource-based view, which emphasizes the importance of resources and capabilities in a firm's competitive advantage. Jobs and salaries can be seen as a measure of the human capital transferred to the host country, contributing to the development of local capabilities and resources, while capital expenditure and investment can be seen as a measure of the physical capital transferred, which may not necessarily lead to the development of local capabilities and resources; 3) stakeholder theory, which suggests that firms have responsibilities to different stakeholders, including the local community, employees, and the environment. Jobs and salaries can be seen as an indicator of the positive impact that FDI can have on the local community and employees, while capital expenditure and investment can be seen as an indicator of the negative impact that FDI can have on the environment; and 4) economic growth theories, which suggest that FDI can contribute to economic growth and development by increasing productivity, generating employment, and promoting technological progress. Jobs and salaries can be seen as an indicator of the positive impact that FDI can have on productivity and employment, while capital expenditure and investment can be seen as an indicator of the negative impact that FDI can have on the balance of payments.

Overall, the proposed MCDM model for measuring FDI performance at the country level is based on several theoretical frameworks. The model provides a comprehensive evaluation of FDI performance by taking into account multiple criteria, which can provide a more nuanced understanding of the impact of FDI on the host country. The proposed model differs from other studies on FDI in several ways. Firstly, it provides a more comprehensive evaluation of FDI than studies that focus on a single criterion or framework. Secondly, the model focuses on evaluating FDI performance at the country level and incorporates the perspectives of various stakeholders, which allows for a broader and more holistic evaluation of the impact of FDI on the host country. Finally, the model uses a MCDM approach, which allows for a systematic and transparent evaluation of FDI performance based on multiple criteria.

Overall, these unique features of the proposed model can help overcome the limitations of traditional methods that rely on subjective judgment or a single criterion. By providing a more comprehensive and nuanced evaluation of FDI performance at the country level, the proposed model can help policymakers and investors make more informed decisions that consider the interests of all relevant stakeholders.

We distinguish ourselves from other previous studies by capturing the influence of socio-demographic drivers on FDI performance through a novel robust stochastic regression based on three major assumptions about the distribution of FDI performance scores: Tobit, Beta, and Simplex. Our proposed model differs from previous studies in that it considers different distribution assumptions of performance scores, which generates more precise results in determining the influence of social-demographic drivers. Previous literature studies have used multiple regression analysis, but our proposed model offers a more robust approach.

Firstly, the Tobit regression technique is utilized to estimate the linear associations between variables when the dependent variable is subject to censoring. The regression method was initially introduced by Tobin (1958). In situations involving left censoring, values that fall at or below a predetermined threshold are censored, while values above the threshold are assigned the threshold value. On the other hand, in the general model, the dependent variable is censored from both above and below simultaneously. For a more comprehensive understanding, refer to McDonald and Moffitt (1980).

Secondly, the simplex distribution is a suitable choice for modeling proportional outcomes. It offers a range of distributions with domains spanning from 0 to 1, making it well-suited for analyzing continuous proportional data. The simplex generalized linear model (SGLM) is employed for statistical inference, utilizing maximum likelihood estimation on a cross-sectional dataset with proportional values. An extension of Jørgensen's work (1997) can be reflected by the Simplex generalized linear model. In most cases, an iteratively re-weighted least squares algorithm is used to optimize the likelihood of the parameters when the parameters β and γ for the SGLM with varying dispersion are estimated. Zhang et al. (2016) provided further details.

Thirdly, when variables are confined to the standard unit interval (0, 1), the Beta regression is used. It is assumed that the dependent variable follows a beta distribution. The Beta regression model incorporates regression parameters that can be interpreted in terms of the mean of the variable of interest. Moreover, the beta density can exhibit various shapes depending on the combination of parameter values, making the Beta regression model highly flexible. The parameterization of the densities is determined by the mean μ and the precision parameter $\varnothing$. Cribari-Neto and Zeileis (2010) provided detailed discussions on Beta regression.

Finally, most of the FDI literature focuses on the endogenous sources – at the country level – for attracting FDI, such as economic growth, individual comparative and competitive advantages, etc. This study, however, focused on the dyad of origin and destination countries in terms of the main features of the investment projects, which is the cornerstone of the analysis. Hence, this paper innovates by exploring how the socio-demographics of both donor and recipient countries, their similarities and differences, may affect not just the FDI volume but also the characteristics of each individual investment project. As for the data modeling in the first and second stages, a fixed panel approach was avoided, not only with respect to unbalanced origin/destination countries over the years but also with respect to a better fit towards the very nature of this dataset, which could be conceptualized as a random draw of countries, years, and investment project characteristics.

Results indicate that the performance of FDI is mixed but low in Jordan and Vietnam, and relevant improvements should be made. Our second-stage analysis reports that higher GDP per capita and good social welfare, including lower infant mortality and higher life expectancy level, contribute to the improvement in FDI performance. Furthermore, it is found that a large percentage of women in the total population, wealth concentration in the destination country, as well as the degree of urbanization, are helpful in improving FDI performance. Finally, we find that FDI performance is mainly concentrated in high-tech and high-value-added industries.

The rest of this paper is structured as follows. Section 2 focuses on the literature review and the methodological research gap. Section 3 depicts the RoCo and robust regression methodologies, as well as the dataset. Data analysis and discussion of results are given in Section 4. Section 5 provides the concluding remarks as well as managerial and policy implications.

2. Literature review

Over the past few decades, there have not been many studies investigating the performance of FDI. Chen (2012) investigated Taiwanese FDI in China in terms of the influence of entry mode choices (i.e., wholly owned subsidiaries versus joint ventures) on the performance of FDI. Using two different performance indicators, namely the average sales growth rate of the subsidiary in the periods following the mode decision and unmeasured profitability of the subsidiary under two different econometric models including treatment effects model and bivariate probit model, the study found that higher sales growth and profitability were observed for the wholly owned subsidiary. It further shows that for the mode choice of joint ventures, the subsidiary with smaller size and the firm with less experience performs better. Similar studies investigating entry mode and performance were also conducted by Nitsch et al. (1995) and Nitsch et al. (1996).

Instead of focusing solely on the performance at the subsidiary or firm level, Dupasquier and Osakwe (2006) examined the performance of FDI at a country level. Two different performance indices were used, including the inward FDI performance index, which was calculated as the ratio between the country's share in global FDI flows and its share in global GDP, and the FDI potential indices, which were computed as the unweighted average of normalized values of several macroeconomic indicators, including GDP growth rate and GDP per capita, among others. Rather than conducting an econometric analysis, they evaluated the determinants of FDI performance through a systematic analysis of relevant literature. The findings suggest that FDI performance can be improved by strengthening infrastructure, increasing economic growth, improving macroeconomic and political stability, as well as creating a more hospitable regulatory environment.

Lyles et al. (2014) assessed the performance of Chinese outward FDI, with an emphasis on the intermediate role played by learning. Two hundred interviews were conducted to derive the performance indicator reflecting the degree to which the firm achieved its goals from seven different perspectives, including reputation enhancement, technology access, and cost reduction. The results from Heckman's two-step analysis showed that what the firm learns from outward FDI plays an intermediate role in the relationship between the firm's potential absorptive capacity and the performance of its outward FDI. Another study was conducted by Wang et al. (2009), examining the relationship between expatriate utilization and FDI performance, with an emphasis on the intermediate role played by knowledge transfer. Two different performance indicators were employed through a survey. The first one is the level of satisfaction, measured by the extent to which the respondent is satisfied with the subsidiary's performance. The second one is the overall performance index, which is calculated as the weighted average of the extent to which the subsidiary has improved its management capabilities, technological capabilities, management localization, growth, and profitability. The results from the multiple regression analysis show that using expatriates with technical skills not only directly affects subsidiary performance but also has an indirect effect on performance via knowledge transferred into the subsidiary.

Makino et al. (2004) comprehensively evaluate Japanese foreign investment performance in 150 countries between 1991 and 1999 by comparing it between less developed and developing countries, and across different industries. Like Lyles et al. (2014), the financial performance indicator was derived by asking top Japanese managers in each subsidiary to specify one of three possible financial performance categories: negative profits, positive profits, or neither negative nor positive profits. The findings show that Japanese FDI in less developed countries grew more rapidly, particularly in the secondary industrial sector. Japanese FDI in developed countries maintained stable growth, particularly in the tertiary industrial sector. Siripaisalpipat and Hoshino (2000) used a similar approach to derive the financial profitability of FDI.

The performance of FDI from Singapore was evaluated by Pangarkar and Lim (2003). The study used a survey to derive the performance indicators, including overall success, stability, sales growth, market share, and profitability achieved by the subsidiary. All these indicators take the form of a rating on a Likert scale. The results indicate that Singaporean firms' foreign subsidiaries achieve a moderate level of performance. The findings from the second-stage multiple regression analysis show that the host country government's attitude and larger subsidiary size compared to the parent firm exert a significant and positive influence on FDI performance.

Based on a panel of bilateral FDI stocks from 10 Western to 10 Eastern European countries over the period 1996–2007, Stack et al. (2015) investigated the performance of FDI and its determinants. The study distinguished itself from other studies by estimating the performance of FDI by transferring the KK (knowledge-capital) model proposed by Carr et al. (2001) into a parametric stochastic frontier analysis. The findings suggest that there is mixed performance of FDI in the sample. In terms of the determinants of the performance, the results suggest that infrastructure development and the process of liberalization exhibit a significant impact.

Using the input distance function with three inputs – labor, domestic capital, and foreign capital – and one output (GDP), Wu et al. (2000) investigated the performance of China's FDI between 1993–1995. The results showed that the performance of FDI in China experienced an inverted J-shaped learning process. Efficient utilization of foreign capital was observed for all regions with less than 3% FDI overutilized. It was argued that the performance was possibly attributed to infrastructure development, the growth of the non-state sector, as well as economic reform. The study suffers from the limitation that no second-stage analysis was conducted to check the accuracy and robustness of the results to support its argument regarding the determinants of FDI.

There have been a number of studies published in the research area of MCDM models during the recent couple of years, applied to various contexts, including investigating air pollution assessment, evaluating bank performance, selecting supply chain management contracts, and developing supply chain resilience, among others (Hadi-Vencheh et al., 2021; Maredza et al., 2022; Yazdi et al., 2022, 2023). More specifically, Hadi-Vencheh et al. (2021) proposed a group MCDM model that ranks the overall preference of decision makers (DMs) using the possibility concept. The method proposed overcomes the disadvantage of previous approaches by providing straightforward and practical computations on ranking the alternatives.

Maredza et al. (2022) introduced a three-stage MCDM model aimed at evaluating the interconnection between bank performance and social welfare. In the first stage, unbiased weights for the criteria were determined using a robust SWARA order-rank approach. Moving to the second stage, the performance score was computed using TOPSIS and COPRAS methods. Finally, in the third stage, an innovative stochastic structural relationship non-linear program was proposed.

MCDM models were also proposed and applied to supply chain management. Yazdi et al. (2022) proposed a MCDM method with gray numbers to rank contracts in the oil and gas industry. The research was conducted through four main stages: 1) identification of factors for selecting supply chain management contract based on previous literature; 2) selection of the most appropriate factors through the Delphi method; 3) determination of primary weights of factors through the grey Best-Worst method (BWM); and 4) provision of rankings for contracts by the grey Measurement of alternatives and ranking according to COmpromise solution (GMARCOS) method.

Another piece of research was undertaken by Yazdi et al. (2023), in which the critical success factors for supply chain resilience in selecting transportation service providers were examined. Similar to Yazdi et al. (2022), the Delphi method was used to identify the critical success factors, while the main innovation of the study lies in the use of BWM and Multi-attributive Border Approximation Area Comparison (MABAC) methods to rank resilience-related CSFs.

The literature has also examined the socioeconomic factors and their impact on different industries (Wanke et al., 2023b; Antunes et al., 2023a, 2023b; Zhao et al., 2022). More specifically, in the banking context, Wanke et al. (2023b) investigate the impact of a series of contextual variables, including inflation, human development index, GDP growth, infant mortality, life expectancy, and energy use on bank efficiency through a generalized linear autoregressive moving average model. Compared to other methods, the proposed model is more flexible, easy to estimate and interpret. In the healthcare context, Antunes et al. (2023a) examine the impact of a number of socioeconomic factors, including GDP, illiteracy, disposable income, sewer, gas pollution, and mortality rate, on healthcare performance in China through machine learning techniques. Similar techniques were also applied by Antunes et al. (2023b) to investigate a number of socioeconomic factors, including research and development expenses, FDI, paved road, GDP per capita, population density, innovation index, and second industry share, on road transportation sustainability performance in China. Zhao et al. (2022) investigate the impact of socioeconomic factors on the Chinese energy production chain through a neural network analysis. The factors considered include birth rate, consumer price index, passengers using different transport modes, students in different levels of education, and urban population, among others.

In summary, the literature on performance evaluation in FDI lacks consideration and exploration of MCDM in the area. Thus, the results or findings of FDI performance from existing studies do not provide accurate and robust results. The existing literature on MCDM models has attempted to assess the issue of uncertainty in performance evaluation. However, no study has yet considered the solution/interaction among different MCDM methods and their underlying assumptions, which we believe would impact the performance scores. Finally, in terms of the investigation into the impact of different socio-economic factors on performance, no study has yet considered the impact of different distribution assumptions of performance scores. Our study fills in these gaps.

3. Methodology

3.1. The data

Descriptive statistics on the dataset are presented in Tables 1, 2, and 3. To enhance readability, criteria and contextual variables were reported based on the nature of their scale, whether scalar or binary. Additionally, readers should note that the terms "source" and "destination" that may appear in the description of some contextual variables refer to whether a given variable is related to the FDI source country or the FDI destination country.

Positive criteria used in RoCo modeling to evaluate FDI performance include new jobs, safeguarded jobs, and average salary. Conversely, negative criteria for FDI performance include CAPEX, amount, incentive per job, and incentive per CAPEX. The objective is to measure FDI performance in terms of generating the highest possible number of well-paid jobs using the lowest possible capital expenditures, investments, and incentives. The underlying hypotheses relate to the impact of socio-economic and project-related contextual variables on FDI performance defined in these terms, as well as specific country effects not captured by them.

Socio-economic variables include, for both source and destination countries: gross domestic product based on purchasing power parity (GDP PPP), Human Development Index (HDI), population, rural population, inflation, mortality rate, women population, life expectancy, and unemployment rate. These variables reflect distinct aspects of demography (rural and women population), social welfare (HDI, mortality rate, and life expectancy), and economic stability (GDP PPP, inflation, and unemployment rate). While social welfare and economic stability may be positively related to some extent to FDI performance in generating numerous well-paid jobs with minimal investments, older demographic pyramids or predominantly rural societies may exert a negative impact on FDI performance.

A large rural population can benefit FDI by providing cheap labor for investment activities. This positive impact of rural population on FDI is confirmed by Paul et al. (2021). Women also play an important role in FDI activities, especially in light manufacturing and service industries (Abramo & Valenzuela, 2005). Moreover, FDI can benefit from women labor due to lower labor costs (Seguino, 2010). Social welfare, represented by HDI, mortality rate, and life expectancy, is expected to have a positive impact on FDI. Dehshiri et al. (20112) argue that the human development index is one of the decisive factors that influence the absorption of FDI. Higher GDP PPP indicates a higher level of personal wealth, which can increase labor costs. Conversely, a higher level of inflation reflects an increase in the general price level, which can increase the cost of operation. Therefore, these variables are expected to have a negative impact on FDI performance. The negative impact of these two variables on FDI is confirmed by Sabir et al. (2019). A large amount of unemployment may force the government to provide more favorable policies to foreign investors, resulting in possible tax benefits or subsidies that can improve FDI performance.

On the other hand, project-related variables include the age of the project (captured by linear and squared components), the project type (new, expansion, or retention), the industry sector (cf. Table 2), and other variables related to the discretion of the destination country, such as the existence of a free zone or alternative types of incentives, such as deferred taxes or subsidized loans, for instance. New projects in capital-intensive and/or high-tech industries may present superior performance than other types of projects. Conversely, older projects, particularly those that are labor-intensive, may clearly suffer from diminishing returns to scale. High-tech industries are regarded as the pillar industries in the economy, and FDI in these industries can benefit the country from the perspective of technology/knowledge spillover. The government will give favorable policies to these investment opportunities (Liu & Zou, 2008). Manjappa and Mahesha (2008) argue that flows of FDI towards capital-intensive industries would contribute to the improvement in total factor productivity.

However, the literature remains inconclusive as to the best type of local incentive for boosting FDI performance, which may be obfuscated by other specifics of the country that are not contemplated in the aforementioned variables. Specifically, although Tung and Cho (2001) find that tax incentives are helpful in attracting FDI inflows, Beyer (2002) disagree and argue that tax incentives do not have any significant impact on FDI. Subsidies would be very helpful to companies in engaging in innovative activities (Gorg & Strobl, 2007), which further leads to a reduction in the cost of operation and an improvement in performance. However, subsidized loans are regarded as a direct drain on government budgets and are not typically granted by developed countries to foreign investors (Lim, 2005). Table 3 provides an idea of the relative importance of each country as an FDI source or destination, and these figures somehow may embed economies of learning, scale, and scope that favor FDI performance.

Table 1. Descriptive statistics for scalar data

Variables	Unit	Type	Min	Max	Median	Mean	SD	CV	Skewness	Kurtosis
CAPEX	USD	n	0.00	21000.00	8.30	66.53	439.08	6.60	28.53	1083.90
Amount	USD	n	0.00	3482.00	0.40	6.66	69.37	10.41	30.31	1164.80
Incentive per CAPEX	% of CAPEX	n	0.00	153.80	0.02	0.18	1.93	10.98	72.17	5713.90
Incentive per job	USD	n	0.00	24166666.67	5402.08	40585.72	384591.84	9.48	48.18	2740.91
New Jobs	Unit	p	0.00	20000.00	62.00	206.05	597.70	2.90	12.69	271.46
Safe guarded jobs	Unit	p	0.00	8000.00	0.00	40.42	284.42	7.04	16.09	327.87
Avg. salary	USD	p	0.00	426720.00	0.00	4898.78	17508.69	3.57	5.70	65.95

End of Table 1

Variables	Unit	Type	Min	Max	Median	Mean	SD	CV	Skewness	Kurtosis
GDP PPP Source	USD (Log)	sc	23.16	30.78	28.80	28.60	1.32	0.05	–0.55	0.22
GDP PPP Destination	USD (Log)	sc	22.83	30.78	28.83	28.76	1.85	0.06	–0.62	–0.79
HDI Source	–	sc	0.35	0.95	0.91	0.89	0.07	0.08	–2.63	7.13
HDI Destination	–	sc	0.34	0.95	0.91	0.86	0.09	0.11	–1.58	2.32
Population Source	Persons (Log)	sc	12.67	21.05	18.20	18.04	1.47	0.08	–0.33	0.52
Populacao Destination	Persons (Log)	sc	12.70	21.05	18.79	18.37	1.45	0.08	–0.77	–0.38
Rural Pop. Source	%	sc	0.00	0.82	0.19	0.21	0.12	0.58	1.72	3.95
Rural Pop. Destination	%	sc	0.02	0.83	0.19	0.26	0.14	0.53	1.76	2.49
Inflation Source	%	sc	–0.08	0.40	0.02	0.02	0.02	1.44	5.40	58.38
Inflation Destination	%	sc	–0.19	0.75	0.02	0.03	0.04	1.56	7.92	104.94
Infant Mortality Rate Source	% per births	sc	0.00	0.07	0.00	0.01	0.01	1.18	4.56	23.60
Infant Mortality Rate Destination	% per births	sc	0.00	0.08	0.01	0.01	0.01	0.92	3.39	13.99
Women Pop. Source	%	sc	0.25	0.54	0.51	0.51	0.01	0.03	–12.01	207.27
Women Pop. Destination	%	sc	0.25	0.54	0.51	0.51	0.02	0.04	–8.58	88.27
Life Expectancy Source	Years	sc	53.43	84.10	81.16	80.46	3.39	0.04	–2.46	8.54
Life Expectancy Destination	Years	sc	51.70	84.10	78.54	77.47	3.55	0.05	–2.26	8.41
Unemploy-ment Rate Source	%	sc	0.14	27.58	5.30	6.41	3.46	0.54	2.64	10.24
Unemploy-ment Rate Destination	%	sc	0.49	27.52	6.17	6.84	4.02	0.59	2.28	8.18
Project Age	–	c	3.14	11.06	6.64	6.68	2.15	0.32	0.21	–1.02
Project Age Squared	–	c	9.88	122.28	44.15	49.29	30.08	0.61	0.64	–0.67

Note: p – positive criterion; n – negative criterion; sc – Socio-economic contextual variable; c – Project-related scalar contextual variable.

Table 2. Distribution of frequencies for project-related contextual dummy variables (c_dummy)

Type	Variable	%
Project Type	Expansion Project	49.51
	New Project	49.06
	Retention	1.44
Freezone	No	82.93
	Yes	17.07
Incentive Type	Grant/Subsidy	41.51
	Loan/Credit	5.04
	Non-financial	0.94
	Unspecified	5.61
	Tax	56.95
Industry Sector	Aerospace, Defence and Marine (ADM)	3.74
	Automotive	22.07
	Basic Materials	11.73
	Consumer Goods	10.92
	Creative Industries	2.50
	Electronics	5.78
	Food & Drink	7.25
	Industrial Goods	13.50
	Information Technology & Telecom (ITT)	5.51
	Leisure & Tourism	0.79
	Life Sciences	6.45
	Non-Renewable Energy	0.87
	Renewable Energy	2.36
	Services	6.53

Note: * Project-related dummy contextual variable.

Table 3. Distribution of frequency for country destinations and sources (c_dummy*)

Country	Source (%)	Destination (%)	Country	Source (%)	Destination (%)
Afghanistan	0.03	0.00	Norway	0.63	0.01
Argentina	0.10	0.69	Oman	0.03	0.27
Australia	1.17	1.06	Pakistan	0.03	0.00
Austria	1.51	0.06	Panama	0.11	0.10
Azerbaijan	0.04	0.03	Paraguay	0.03	0.28
Bahamas	0.01	0.00	Peru	0.07	0.07
Bahrain	0.01	0.23	Philippines	0.06	0.28
Bangladesh	0.01	0.56	Poland	0.31	3.55
Belarus	0.04	0.28	Portugal	0.23	0.37
Belgium	1.38	0.16	Qatar	0.01	0.00
Bosnia and Herzegovina	0.03	0.01	Romania	0.10	0.92

Continue of Table 3

Country	Source (%)	Destination (%)	Country	Source (%)	Destination (%)
Brazil	1.00	1.75	Russia	0.35	2.14
Brunei	0.01	0.07	Saudi Arabia	0.07	0.06
Bulgaria	0.03	0.11	Singapore	0.66	0.00
Canada	5.91	3.77	Slovakia	0.04	1.00
Chile	0.10	0.23	Slovenia	0.16	0.24
China	4.01	0.20	South Africa	0.35	0.89
Colombia	0.20	0.55	South Korea	0.38	0.04
Costa Rica	0.04	0.82	Spain	1.88	1.20
Croatia	0.03	0.00	Sri Lanka	0.03	0.18
Cyprus	0.07	0.00	Sweden	1.88	0.04
Czech Republic	0.16	4.34	Switzerland	4.29	0.00
Denmark	1.07	0.23	Tanzania	0.01	0.03
Ecuador	0.03	0.32	Thailand	0.37	5.01
Egypt	0.06	0.06	Trinidad and Tobago	0.01	0.00
El Salvador	0.06	0.06	Tunisia	0.04	0.00
Finland	0.79	0.03	Turkey	0.56	0.31
France	5.71	0.89	UAE	0.17	0.49
Germany	14.40	0.68	Uganda	0.01	0.00
Greece	0.01	0.00	UK	7.02	5.30
Guatemala	0.06	0.00	Ukraine	0.04	0.00
Honduras	0.01	0.00	Uruguay	0.01	0.06
Hungary	0.06	2.12	USA	13.29	45.95
Iceland	0.06	0.01	Uzbekistan	0.01	0.07
India	2.37	1.11	Venezuela	0.07	0.00
Indonesia	0.10	0.21	Vietnam	0.06	0.55
Iran	0.04	0.03	Algeria	0.00	0.01
Ireland	1.64	0.16	Armenia	0.00	0.03
Israel	0.78	0.03	Bolivia	0.00	0.01
Italy	3.61	0.23	Cambodia	0.00	0.32
Japan	15.11	0.01	Dominican Republic	0.00	1.14
Jordan	0.01	0.01	Estonia	0.00	0.16
Kenya	0.01	0.07	Fiji	0.00	0.01
Kuwait	0.04	0.00	Gabon	0.00	0.07
Latvia	0.03	0.11	Ghana	0.00	0.06
Lebanon	0.04	0.03	Jamaica	0.00	0.07
Lithuania	0.04	0.34	Kazakhstan	0.00	0.03
Luxembourg	0.83	0.01	Laos	0.00	0.06
Malaysia	0.31	0.49	Moldova	0.00	0.25

End of Table 3

Country	Source (%)	Destination (%)	Country	Source (%)	Destination (%)
Malta	0.03	0.00	Mozambique	0.00	0.01
Mexico	0.78	2.03	Myanmar	0.00	0.59
Morocco	0.01	1.09	Nicaragua	0.00	0.45
Nepal	0.01	0.00	Rwanda	0.00	0.07
Netherlands	2.09	0.00	Serbia	0.00	1.69
New Zealand	0.49	0.01	Zambia	0.00	0.13
Nigeria	0.03	0.13			

Note: * Project-related dummy contextual variable.

3.2. Robust compromise MCDM (RoCo MCDM)

Consider a set F comprising k unique MCDM models employed for ranking alternatives. Each function f_k (.) associated with these MCDM models generates a performance score vector pk as its output, containing scores for each of the m alternatives. These functions take inputs including a weight vector w, an mxn matrix R, and a vector s. The values for the n criteria are represented by w, each alternative's normalized criterion values make up the matrix R, and each of the n criteria's sign description is included in s. Thus, the relationship can be expressed as follows:

$$f_k\ (\mathrm{w, R, s}) = \mathrm{p}_k. \quad (1)$$

In contrast, consider a set G comprising l unique MCDM models employed for weighting criteria, such as AHP, SWARA, and others. Each function g_l (.) associated with these MCDM models produces a weight vector w_l as its output, containing values for each of the n criteria. The input for each function is an mxn matrix X consisting of each alternative's original criterion values, which can be optionally normalized into an R matrix on the basis of the chosen approach. Thus, the relationship can be described as follows:

$$g_l\ (\mathrm{X\ or\ R}) = \mathrm{w}_l. \quad (2)$$

Consider a vector W of size k, which signifies the weights assigned to each f_k (.) function within the set F. Genetic algorithms provide a viable approach for solving the RoCo non-linear program and determining the optimal values of both W and w. This involves utilizing genetic algorithms to search for the most favorable solutions.

$$\text{Minimize: } \mathrm{W}^{\mathrm{T}} * Cov(f_1\ (\mathrm{w, R, s}), \ldots, f_k\ (\mathrm{w, R, s})). \quad (3)$$

Subject to:

$$\mathrm{w.min} \le \mathrm{w} \le \mathrm{w.max}; \quad (4)$$

$$\sum\nolimits_k W_k = 1; \quad (5)$$

$$\sum\nolimits_n w_n = 1. \quad (6)$$

Using each MCDM model in F, we calculate the weighted covariance matrix of the performance, which is represented by the objective function. furthermore, the vectors of length n estimated by min(g_1(X or R), ..., g_l(X or R)) and max(g_1(X or R), ..., g_l(X or R)) are denoted by w.min and w.max, respectively. The minimum and maximum achievable weights for each criterion are determined by utilizing the MCDM models in G. The constraints specified in Eqs (5) and (6) guarantee that the total sum of weights for all MCDM models and criteria is equal to 1.

3.3. Robust regression on RoCo performance scores

A robust regression approach is used to examine the influence of the contextual variable on FDI performance. Due to the large number of explanatory variables and the inherent collinearity issues, two alternative linear model specifications were considered: one including only scalar explanatory variables, and the other including only explanatory dummy variables.

$$\text{Robust Regression 1: RoCo Performance} = f\text{ (sc, c)}; \tag{7}$$

$$\text{Robust Regression 2: RoCo Performance} = f\text{(c\_dummy)}. \tag{8}$$

In the robust regression approach, for each alternative model specification, Tobit (Wanke et al., 2016a) and Beta (Wanke et al., 2016b) regressions were individually designed to handle dependent variables bounded in 0 and 1. These regression were then combined using stochastic non-linear programming and bootstrapping, as presented in model (9), where ω_1 and ω_2 represent the weights, ranging from 0 to 1, assigned to the vector of residuals of the Tobit regression (R_1) and Beta regression (R_2), respectively.

This model optimizes the value of ω so that the variance (*Var*), covariance (*Covar*) and the mutual information (*MI*) of the combined residuals are minimal with respect to a normal distribution with zero mean and standard deviation equal to the same as these pooled residuals. All regressions were bootstrapped and combined 100 times, allowing for a distributional profile of w to be collected for the best predictions of FDI performance, assuming a linear specification for each regression.

$$\text{Minimize}: Var\left(\sum_{i=1}^{2}\omega_i * R_i\right) + \Big(2*\big((\omega_1*\omega_2*R_1*R_2\big)*Covar\ (\omega_i*\omega_j*R_i*R_j\Big),$$

$$i \neq j, j < i\Big) + \left(MI\left(\sum_{i=1}^{2}\omega_i * R_i, Norm\left(0, sd\left(\sum_{i=1}^{2}\omega_i * R_i\right)\right)\right)\right).$$

Subject to:

$$\sum_{i=1}^{2}\omega_i = 1 \qquad \omega_j\text{: free} \tag{9}$$

$$0 \le \omega_i \le 1 \qquad \text{for all } i.$$

Model (9) was solved using the differential evolution (DE) technique.

The proposed approach tackles two major underlying issues with respect to the application of MCDM. The first issue relates to determining the most suitable model to be adopted, given that various models are available, each with different assumptions embedded within them, such as ideal solutions, trade-offs, and compromise solutions. The epistemic uncertainty surrounding most MCDM problems makes it challenging to identify which assumption is the most appropriate for consideration, given that decision makers need to identify benchmarks, trade-off different criteria, and establish compromise weights between positive and negative criteria. The second issue relates to the non-parametric nature of most MCDM models, where the covariance matrix among criteria is often neglected, leading to biased results in terms of rankings and scores. In contrast, RoCo simultaneously optimizes distinct criteria and model weights in a quadratic programming problem to minimize the covariance matrix among them, allowing individual MCDM results to be manipulated with minimal bias. However, the interpretation of the RoCo results is still straightforward since this model is a non-parametric linear combination of previous established models based on their respective weights. It is worth noting that the statistical properties of the resulting scores are hypothesized and tested within the context of parametric regression approaches for dependent variables (RoCo scores) that are bounded within the range of 0 and 1.

The main objective of the robust regression approach adopted here is to provide an unbiased combination of existing regression approaches while minimizing the covariance of the residuals, particularly when handling dependent variables that are bounded in the 0–1 range. Beta, Simplex, and Tobit are the most commonly used assumptions to regress performance scores onto a set of regressors. Differential optimization is used to optimize the weights of these three regression combinations, minimizing their covariance and improving their explanatory power. The ultimate goal is to obtain an empirical combination of distribution assumptions that more closely resemble the unknown actual distribution of scores generated by the RoCo model.

4. Analysis and discussion of results

The results of the RoCo optimization and its performance scores are presented in Table 4 and Figures 1a, 1b, and 2. As expected, the RoCo scores offer a compromise solution concerning the TOPSIS, VIKOR, and COPRAS scores in terms of mean, standard deviation, skewness, and kurtosis values. However, it is worth noting that the RoCo scores exhibit higher information entropy than all other alternative MCDM models. According to the principle of maximum entropy, the distribution with maximum entropy is considered to be the most suitable representation of the existing knowledge to explain the phenomenon. Maximal entropy ensures unbiased decision-making by incorporating the highest level of diversity in the distributional profiles of FDI performance scores. This approach serves as a robust or extreme scenario, capturing potential unconsidered assumptions during the research design phase. Figure 1a (left) and Figure 1b (left) demonstrate that the RoCo performance scores not only exhibit a bi-modal shape but also show a better balance between score discrimination (excluding the 0 and 1 extremes) and range between their maximal and minimal values compared to other MCDM score distributions.

Table 4. Descriptive statistics for performance scores computed using alternative MCDM

MCDM	Mean	SD	CV	Skewness	Kurtosis	IE
TOPSIS	0.718	0.006	0.008	–17.537	630.364	0.139
VIKOR	0.675	0.017	0.026	–10.942	406.092	0.121
COPRAS	0.035	0.112	3.160	5.423	29.861	0.175
RoCo	0.369	0.048	0.129	4.663	24.038	0.264

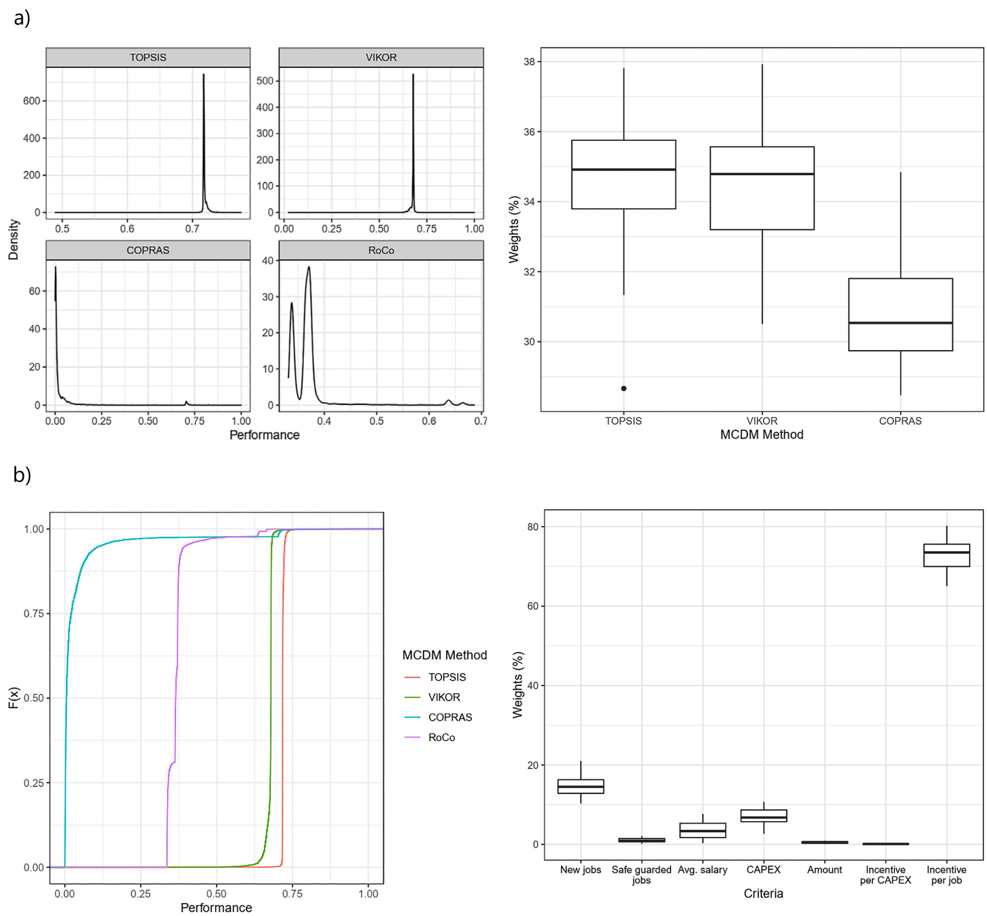

Figure 1. RoCo results: a– MCDM densities (left), optimal MCDM weights (right); b – cumulative distributions (left), and optimal criterion weights (right)

Regarding MCDM weights (Figure 1a, right), TOPSIS and VIKOR accounted for almost 35% of RoCo weights each, followed by COPRAS, with slightly more than 30%. This result indicates that, concerning FDI performance, RoCo scores emphasize trade-offs amongst criteria (VIKOR) and their ideal solutions (TOPSIS) more than their underlying utility functions (COPRAS). In practical terms, the best FDI performers search for business environments where trade-offs between criterion costs and benefits can be more easily managed towards the ideal solution of having more well-paid jobs (thus operations would intrinsically have more value-added) with fewer investment and/or incentive requirements.

On the other hand, concerning criterion weights (Figure 1b, right), incentives per job are the most important one, accounting for around 70%, followed in order by new jobs, CAPEX, and average salary, while the remaining criteria are negligible – safe-guarded jobs, investment amount, and incentive per CAPEX. Given the signs of each criterion, the best FDI performers tend to avoid projects where incentives per job are higher, regardless of the investment amount and whether or not some jobs would be safeguarded. In fact, the best FDI performers seem to be attuned to the synergistic effects that arise between favorable business environments and the local positive externalities geared by CAPEX in terms of well-paid jobs.

Before discussing the robust regression results, it is worth noting the results depicted in Figure 2 for the criterion weight constraints used in RoCo optimization. In fact, AHP and SWARA yielded weights that were similar in magnitude for each criterion, which was reflected in the previous paragraph's discussion.

Figure 3 shows that the distributional weight profiles for both robust regressions are quite similar, with Tobit accounting for more than 75%. For the sake of readability due to the large number of variables, only bootstrapped significant coefficients (at the 5% level) are reported in Figures 4 and 5, for regressions 1 and 2, respectively.

Social-economic variables appear to have an ambiguous impact on FDI performance, which depends on a mix of demographic and social welfare factors in source and destination countries. Superior FDI performance appears to be concentrated in destination countries with higher GDP per capita (high GDP, low population) and good social welfare standards, such as lower infant mortality rates and higher life expectancy levels. Surprisingly, a large percentage of women in the total population also has a positive impact on FDI performance, and a number of explanations could be offered for this phenomenon. First, a higher percentage

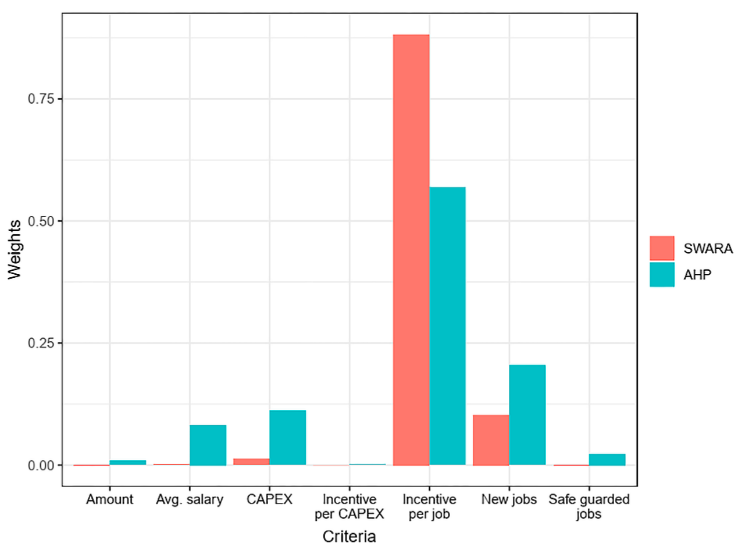

Figure 2. Criterion weight constraints used in RoCo optimization

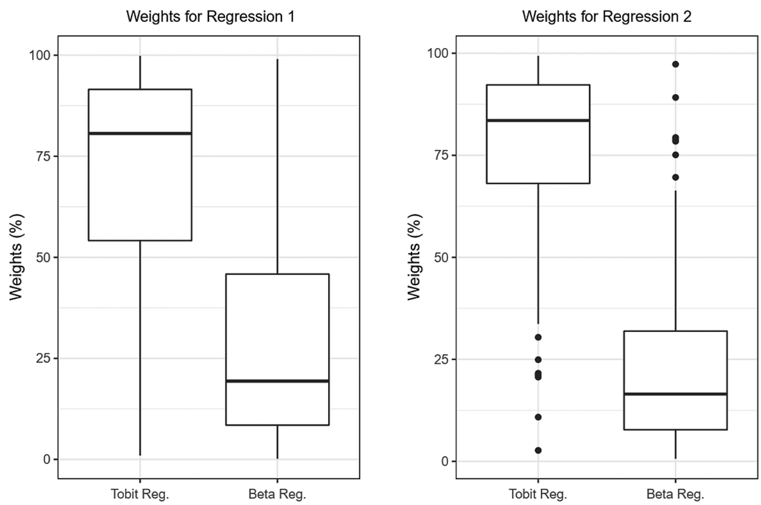

Figure 3. Robust regression weights

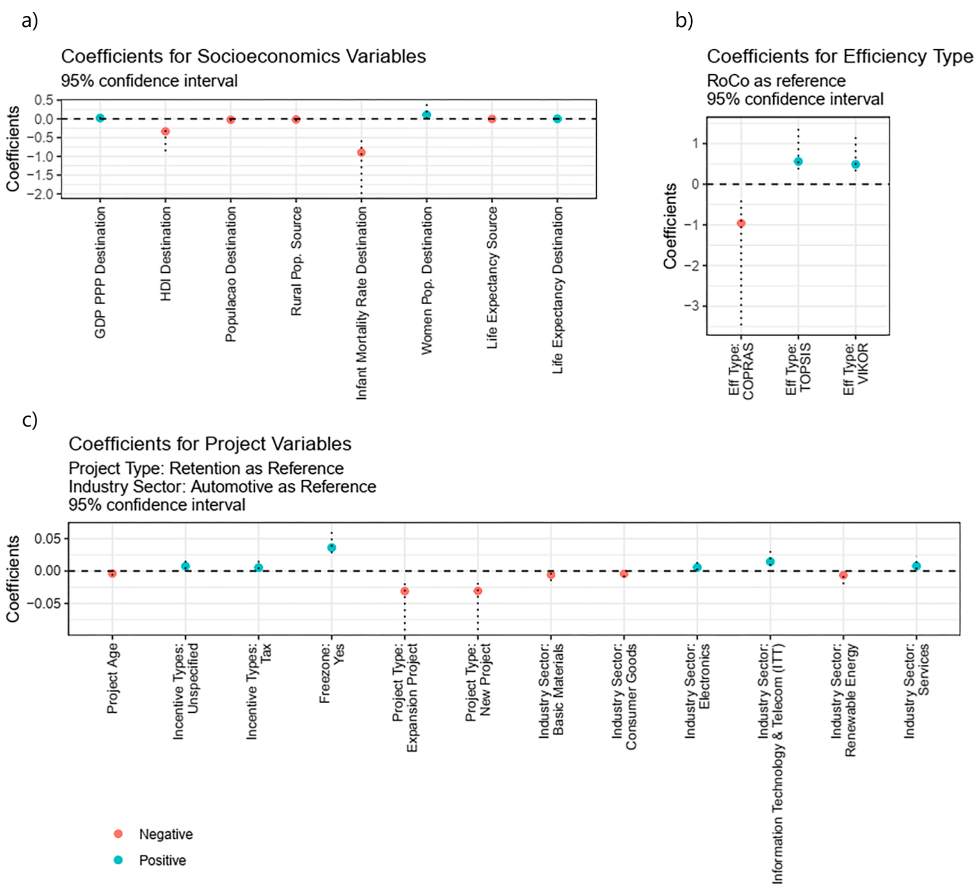

Figure 4. Significant coefficients for regression 1: a – socio-economic variables; b – dummy control for the model type; c – project-related and sector variables

of women in the total population may be a proxy indication of population growth and the capability of the country to renew its population pyramid in the future. While the secondary dataset used lacks consecrated information regarding fertility rate and population migration patterns amongst origin and destination countries, it is possible to hypothesize, by exclusion, that a higher percentage of men would be harmful for population growth for obvious reasons. Second, multinational firms in source countries may be eager to promote gender equality initiatives throughout the world, which may favor the attraction of FDI to certain societies.

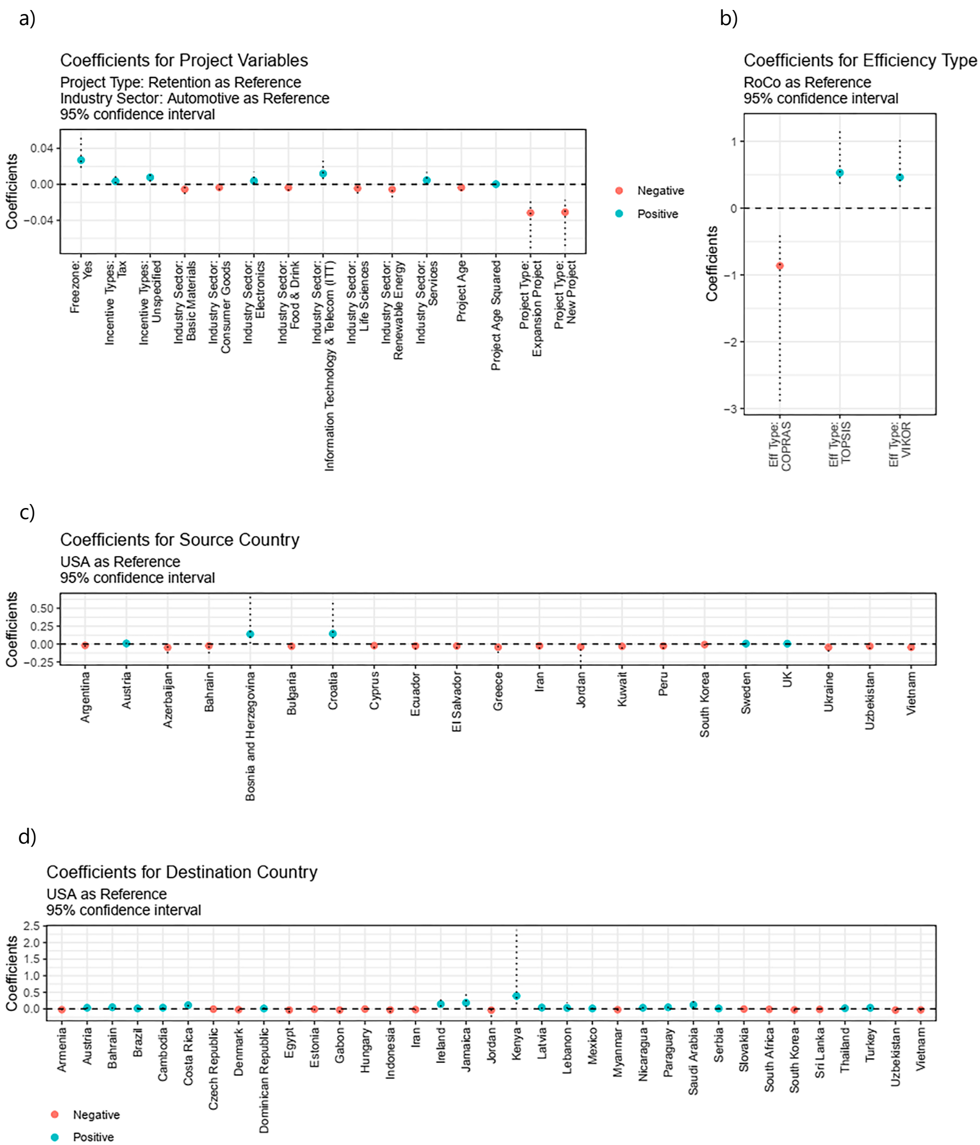

Figure 5. Significant coefficients for regression 2: a – project-related and sector variables; b – dummy control for the model type; c – dummies for source countries; d – dummies for destination countries

Third, women represent a large and underutilized talent pool in many countries, and companies that prioritize gender diversity tend to have access to a wider pool of skilled workers. This can help companies to develop innovative products and services and increase their competitiveness, which can, in turn, attract more foreign investment (McKinsey & Company, 2015). Lastly, the negative impact of HDI on FDI performance suggests that wealth concentration in destination countries, as a means of accumulating capital stock over time, is a positive determinant for higher FDI performance. In fact, fruitful FDI spillovers often require a given destination country to be capable of creating its own local productive network to provide goods and services to the recently installed foreign firm. As regards source countries, a higher percentage of the urban population, as a proxy for a productive and relatively young human capital stock capable of sustaining innovation processes and generating wealth, appears to be the key to higher FDI performance. Therefore, countries should not only focus on economic development, economic sector restructuring, reallocation of resources, but also improve the process of urbanization. It can serve as a tool for the government in further enhancing the performance of their FDI activities. Although different studies applied different methods/indicators to derive the performance, one of the indicators that can reflect the performance well is cost reduction (Lyles et al., 2014). As discussed previously, a higher degree of urbanization can be regarded as an indicator reflecting a higher level of the innovation process, which further promotes cost reduction in investment activities.

Regarding project type and industry (cf. Figure 4), the results suggest that the best performing FDI projects are related to retention projects stimulated by financial incentives, preferably regarding less taxation and free zones rather than subsidized loans offered by destination countries. This means that economies of learning, due to already being installed and operating in a country, are crucial and capable of offsetting the lack of economies of scale and scope during the ramp-up of new and basic projects. Besides, subsidized loans offered by destination countries are not capable of attracting or even retaining projects if there is an excess of capital stock worldwide, eager for new investment opportunities.

Nevertheless, it is interesting to note that the best performing FDI projects are concentrated in high-tech, high value-added sectors, such as electronics, technology, telecom, and services, requiring a well-educated workforce in destination countries to catch up with the necessary knowledge. Our findings suggest that new policies should focus on high-tech and high value-added industries, which would lead to a more optimal allocation of resources. More funding and resources should be devoted to further help the evolution and development of these industries, which generate a higher margin between the price of goods and services and the cost of production, leading to improved performance from a profitability perspective (Chen, 2012). Furthermore, favorable policies in FDI, particularly in the high-tech industries, would encourage technology/knowledge spillovers to both the source and destination countries (Dimitrova et al., 2022).

Regarding the impact of destination and source countries on FDI performance (cf. Figure 5), the paradigmatic case of the USA, as the largest donor and receiver of such investments, was considered the reference category. While a handful of source countries present better performance levels than the US in terms of FDI – including only European countries such as the UK, Sweden, and Austria – as regards the destination countries, this picture is more heterogeneous and appears to be related to the comparative advantages of each country.

One possible reason for the high FDI performance of Sweden, Austria, and the UK is attributed to their relatively higher personal wealth, reflected by the fact that over the period 1998–2014, these three countries have an average GDP per capita of more than $38,000 per year (Paramati et al., 2021). This is in line with our previous finding that GDP per capita has a significant and positive impact on FDI performance. In terms of the destination countries, although the picture is more heterogeneous compared to that of the source countries, in general, higher performance focuses on the less developed countries, although some advanced countries are also included. We argue that this finding can be mainly attributed to the fact that the higher FDI performance of the destination countries benefits more from the technology/knowledge spillover from the FDI activities.

5. Conclusions

FDI is an important topic in the field of international business. Its contributions to the overall economy, as well as various economic sectors, have attracted the attention of government officials, regulatory authorities, and academic researchers. Comprehensive investigations have been conducted using economics and econometric analysis to facilitate relevant evaluations. However, the use of operational research methods in the analysis of international business and FDI has received little attention. There is a lack of research studies devoted to employing the MCDM model in analyzing FDI.

The current study fills the gap in the literature by contributing to the area of operational research and international business. Specifically, the traditional MCDM model is enhanced by proposing a novel robust compromised MCDM model using non-linear programming solved by a genetic algorithm. The study also investigates the performance of FDI under the proposed method, contributing to the literature on international business and FDI. We also contribute to the literature by investigating the performance of FDI by proposing a stochastic robust regression.

Most of the FDI literature focuses on the endogenous sources, at the country level, for attracting FDI, such as economic growth, individual comparative and competitive advantages, etc. This study, however, fills a literature gap by focusing on the dyad of origin and destination countries in terms of the main features of the investment projects, which is the cornerstone of the analysis. Hence, this paper innovates by exploring how the socio-demographics of both donor and recipient countries, their similarities, and differences may affect not just the FDI volume but also the characteristics of each individual investment project. Regarding the data modelling in the first and second stages, a fixed panel approach was avoided, not only with respect to unbalanced origin/destination countries over the years but also to better fit the very nature of this dataset, which could be conceptualized as a random draw of countries, years, and investment project characteristics.

The findings of our study show that the performance score derived from our innovative MCDM model is 0.369, which is much lower than the traditional TOPSIS and VIKOR scores but higher than the one from COPRAS. This suggests that the performance scores generated by

TOPSIS and VIKOR are inflated, and the performance score derived from COPRAS is deflated. Our results suggest that the performance of FDI is relatively low, and relevant improvements should be made.

Our second stage analysis reports that FDI performance is significantly and positively affected by GDP per capita and the level of life expectancy but negatively influenced by infant mortality. Furthermore, it is found that several factors influence FDI performance in a significant and positive manner, including the percentage of women in the total population, wealth concentration in the destination country, and the degree of urbanization. We also find that the best FDI performers tend to avoid projects where incentives per job are higher. Finally, the results show that high-tech and high value-added industries have higher FDI performance.

Our study generates important policy implications: 1) the government should concentrate on improving personal wealth, which could be facilitated by population control or improvement in productivity through technological innovation; 2) more efforts should be given to improving or accelerating the process of urbanization, which can be facilitated by industry restructuring and achieved by reallocating resources and focusing on urban construction and non-agricultural sectors; 3) low FDI performance is concentrated in sectors other than high-tech and high value-added industries, such as the manufacturing industry. Therefore, efforts are recommended to improve the production process and increase the efficiency level of the manufacturing industry; 4) in order to improve FDI performance, investment should focus on projects with lower incentives per job because our results show that the benefit of reducing incentives per job would come with a much larger and stronger effect on cost reduction and have a positive impact on investment performance.

One limitation of this study is related to the use of two secondary datasets, fDi Markets and World Bank Open Data, available at https://www.fdiintelligence.com/fdi-markets and https://data.worldbank.org, respectively, both ranging from 2010 to 2017. While relying on secondary sources may spare considerable effort in collecting, compiling, and standardizing data from different sources, it imposes certain drawbacks with respect to the research design and the hypotheses that can be formulated and tested. Further studies should compile additional variables with respect to other relevant drivers, such as the political system of the origin and destination countries and their market size, to assess their relevance amongst the other variables tested in this research.

Compliance with ethical standards

There is no funding to report for this research.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest

Peter Wanke declares that he has no conflict of interest; Yong Tan declares that he has no conflict of interest; Jorge Antunes declares that he has no conflict of interest; Ali Emrouznejad declares that he has no conflict of interest.

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