Greenfield FDI attractiveness index: a machine learning approach

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Abstract

Purpose – This study aims to propose a comprehensive greenfield foreign direct investment (FDI) attractiveness index using exploratory factor analysis and automated machine learning (AML). We offer offer a robust empirical measurement of location-choice factors identified in the FDI literature through a novel method and provide a tool for assessing the countries' investment potential.

Design/methodology/approach – Based on five conceptual key sub-domains of FDI, We collected quantitative indicators in several databases with annual data ranging from 2006 to 2019. This study first run a factor analysis to identify the most important features. It then uses AML to assess the relative importance of each resultant factor and generate a calibrated index. AML computational algorithms minimize predictive errors, explore patterns in the data and make predictions in an empirically robust way.

Findings – Openness conditions and economic growth are the most relevant factors to attract FDI identified in the study. Luxembourg, Hong Kong, Singapore, Malta and Ireland are the top five countries with the highest overall greenfield attractiveness index. This study also presents specific indices for the three sectors: energy, financial services, information and communication technology (ICT) and electronics.

Originality/value – Existent indexes present deficiencies in conceptualization and measurement, lacking theoretical foundation, arbitrary selection of factors and use of limited linear models. This study's index is developed in a robust three-stage process. The use of AML configures an advantage compared to traditional linear and additive models, as it selects the best model considering the predictive capacity of many models simultaneously.

Keywords Foreign direct investment, Artificial intelligence, FDI determinants, Attractiveness factors, Automated machine learning, FDI index

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1. Introduction

Attracting foreign direct investment (FDI) is a major concern for countries seeking economic development and sustainable growth. In general, there is a positive relationship between FDI flows and world gross domestic product (GDP) growth. FDI involves the transfer across national boundaries of relevant assets besides financial capital. It is an important source of capital, employment, technology, management and organizational skills, entrepreneurship and incentive structures (Dunning and Lundan, 2008; Villaverde and Maza, 2015).

Previous attempts to develop FDI attractiveness indexes by practitioners and scholars have resulted in general indexes, usually lacking a theoretical foundation. They have identified several factors, but there is an absence of a shared understanding of the relevant determinants of FDI. Despite many works approaching FDI determinants, the literature is fragmented and the selection of factors seems arbitrary (Paul and Feliciano-Cestero, 2021). Besides, they use restricted linear models that only account for straight-line relationships between variables and target. Table 1 summarizes the theoretical foundation (when applicable), data, categories, scope, method and main results of previous indexes.

This article aims to overcome these deficiencies in conceptualization and measurement by developing an FDI attractiveness index through a robust three-stage process. Our index is based on critical factors identified in a comprehensive FDI attractiveness conceptual model (Bretas *et al.*, 2021), confirming their impact on FDI. We focus on greenfield investments, proposing a calibrated index through exploratory factor analysis (EFA) and automated machine learning (AML). More precisely, we run a factor analysis to identify the most relevant features. Then, we use AML to attribute weights to the resultant factors and generate the consolidated index. AML is an artificial intelligence class of models that find the optimal solutions between a set of variables (predictors) and a target (in this case, FDI). Through AML, we can explore complexity using big data and validate theoretical patterns derived from the data.

We seek to provide a tool for scholars, practitioners and policymakers to assess the countries' potential for greenfield investment. We also take a closer look into three strategic economic sectors, energy, information and communication technology (ICT) and electronics and financial services, presenting specific indexes for each one. These sectors offer great opportunity potential for investors and are essential for achieving sustainable development and faster post-COVID-19 recovery. We contribute to FDI research as, to our knowledge, this is the first study that uses AML to construct an FDI attractiveness index.

The use of AML configures an advantage compared to traditional linear and additive models, as it selects alternative models freely, based on the data characteristics and predictive capacity of many models simultaneously. Fields lacking a shared understanding of the exact predictors and their relationship with the target variables can benefit from AML algorithmic learning. AML minimizes predictive errors, explores patterns in the data and makes predictions based on these patterns in an empirically robust way, comparing the predictive performance of various models (Doornenbal *et al.*, 2021).

The remainder of the paper is organized as follows. Section 2 presents the theoretical background. Section 3 shows the methodology adopted to construct the general and sectoral attractiveness FDI indexes. Section 4 presents the results for factor analysis, AML and calibrated overall and sectoral indexes. Finally, in Section 5, we offer the discussion and conclusions of the study.

Table 1. FDI indexes

Index	Theoretical foundation	Data	Categories	Scope	Method	Results
Kearney Foreign Direct Investment (FDI) Confidence Index	N/A	Primary data from a survey with 500 senior executives of the world's leading corporations (annual revenues of $500mn or more)	N/A	30 countries	Rankings are calculated based on questions about the companies' likelihood of direct investment in a country over the next three years	The USA, Canada and Germany are the most attractive countries for FDI
GFICA index	Empirical literature on FDI determinants	60 quantitative indicators from several databases	Three major axes (prerequisites, underlying factors and externalities)	109 countries	Consistency analysis, normalization, weighting and aggregation	The USA, Switzerland and Sweden are the most attractive countries for FDI
Global attractiveness index	N/A	Quantitative indicators from several databases	Four sub-indexes: positioning index, dynamism index, sustainability index, growth expectations	148 countries	Database processing, winsorization of data, data normalization and aggregation. Reconstructs its series from past data to reflect in each year's report the updates issued by the international statistical bodies	The USA, Germany, and China are the most attractive countries for FDI
FDI attractiveness scoreboard	Dunning (1998)	18 quantitative indicators from several databases	Four different aspects of the investment climate: political, regulatory and legal environment, infrastructure and good market access, knowledge and innovation capacity and cost competitiveness	44 countries	The overall score is the simple average of the country's equivalent score across the four sub-indexes that, in turn, is the average score across the indicators included in each subindex	Hong Kong, Switzerland and Finland are the most attractive countries for FDI, whereas Kuwait, India and Brazil are the least attractive
EY attractiveness survey	N/A	EY European Investment Monitor (EIM) – database that tracks FDI projects that have resulted in the creation of new facilities and jobs	Image, investor confidence and the perception of a country's or area's ability to provide the most competitive benefits for FDI	550 international decision-makers investing in Europe	Investment announcements, the number of new jobs created and, where identifiable, the associated capital investment/field research via online surveys	France, the UK and Germany are tied as Europe's top investment destinations

(continued)

Index	Theoretical foundation	Data	Categories	Scope	Method	Results
Global EDGE market potential index (MPI)	N/A	In total, 23 quantitative indicators from several databases – not focused on FDI	Eight dimensions are chosen to represent the market potential of a country on a scale of 1–100	97 countries	The relative weights of the dimensions are determined by a Delphi process of international business professionals and educators. The seven dimensions are combined into the overall index by using the corresponding weights	Rank with a US focus (the USA not included as destination). China, India and Singapore are the best performing countries
Greenfield Performance Index	N/A	Greenfield FDI data used in the index is derived from FDI markets	Performance – FDI projects	84 countries	Methodology devised by Unctad for overall FDI applied to greenfield FDI	Costa Rica, Lithuania and the UAE are the best performers, whereas China and Japan stand out as the lowest performing countries

Table 1.

2. Theoretical background

2.1 Foreign direct investment motives and location choices

The ownership, location and internalization (OLI) eclectic paradigm is a holistic theoretical framework that seeks to explain FDI in terms of three types of advantages that multinationals possess, ownership , location and internalization (Dunning, 1977). According to it, the locational preferences and determinants that attract firms to specific locations are related to the motives for the investment or type of FDI. Four main types of FDI are identified, resource-seeking, market-seeking, efficiency-seeking and strategic asset-seeking. Other motives, such as escape investments, are also acknowledged. Multinational companies can engage in multiple types of FDI, and their objectives might change according to the maturity level or degree of internationalization (Dunning, 1998, 1993; Dunning and Lundan, 2008).

Resource-seeking FDI refers to acquiring specific resources, such as natural resources, unskilled or semi-skilled labor, expertise and organizational skills, that cannot be obtained in the home market or have a lower cost in the host country. Market-seeking FDI is related to the objective of supplying goods or services to a country or region when market conditions (tariffs, cost-raising barriers, market size, attraction policies, follow suppliers or customers, among others) justifies local production over exports. Efficiency-seeking FDI motivations consist of rationalizing the structure of established resource-based or market-seeking investment enabling the company to gain from the shared governance of geographically dispersed activities, as observed in economies of scale and scope. Finally, strategic asset-seeking FDI is related to long-term strategic objectives of sustaining or advancing global competitiveness (Dunning and Lundan, 2008).

Cuervo-Cazurra *et al.* (2015) revisited the above classification of FDI motives to provide a theoretically based classification, integrating and refining previous ideas. The authors propose four types of internationalization motives based on behavioral economics: sell more, buy better, upgrade, and escape. The eclectic paradigm (Dunning, 1993; Dunning and Lundan, 2008) and behavioral economics classifications can be integrated, as Cuervo-Cazurra and Narula (2015) show. Sell more refers to firms exploiting existing resources to obtain better host country conditions. It can be associated with market-seeking and efficiency-seeking FDI.

Buy better occurs when firms exploit existing resources and avoid difficult home country conditions. It is related to resource-seeking and efficiency-seeking FDI. Both sell more, and buy better categories are connected with other motives, as trade and finance-supportive investment. Upgrade refers to firms seeking to explore new resources, as it obtains better host country conditions, and it is associated with strategic asset-seeking FDI. Finally, the escape motive refers to firms seeking to explore new resources and avoid difficult home country conditions, in other words, FDI to get away from poor conditions.

2.2 Foreign direct investment attractiveness factors

One of the most researched topics in FDI literature consists of inward FDI determinants or attractiveness factors. Previous studies tried to identify the determinants associated with attracting firms to specific locations under different frameworks and theoretical lenses (Blonigen, 2005; Paul and Feliciano-Cestero, 2021; Villaverde and Maza, 2015). According to Paul and Feliciano-Cestero (2021), the most investigated FDI determinants are market size, government policies, entry barriers, cost of production, wage rate and infrastructure. However, the authors assert that the selection of these factors is somewhat arbitrary.

By examining previous literature reviews and studies on FDI determinants through a bibliometric and content analysis of the most relevant articles on the ISI Web of Science database, Bretas *et al.* (2021) presented a comprehensive conceptual model with five main sub-domains of FDI attractiveness factors: entry conditions, institutional framework, market conditions, resources offer and structure for FDI. The framework considers both risk and classical factors and agglomeration-related aspects (Wheeler and Mody, 1992).

Entry conditions refer to agglomeration effects, openness to FDI and distance. It includes restrictions, tariffs, supporting industries, geographic, administrative and economic distances and others. The institutional framework comprises governance aspects, political regimes, risk and corruption effects on FDI. Market conditions include market-related determinants as the market size and potential, trade agreements and investment promotion. Resources offer involves natural resources, human capital, property protection, technological resources and infrastructure. The structure for FDI includes macroeconomic determinants, such as financial development, taxation and FDI motives.

These five domains are aligned with the eclectic paradigm (Dunning, 1993; Dunning and Lundan, 2008) and behavioral economics (Cuervo-Cazurra *et al.*, 2015) classifications of FDI motives. Firms seeking to sell more, engaged in market-seeking, efficiency-seeking, trade-supportive, finance-supportive or passive investments prioritize host markets offering good market conditions, good access and entry conditions, good access to consumers and production conditions, solid institutional framework and good structure for FDI.

Companies engaged in buying better through resource-seeking, efficiency-seeking, trade-supportive, finance-supportive or passive investments seek host markets with a good offer of natural resources, low-cost labor and infrastructure, good market conditions, good access and entry conditions, robust institutional framework and structure for FDI. Companies with upgrading purposes, engaged in strategic asset-seeking and management-supportive investment, prioritize host markets with a good offer of technological resources, high-skilled labor, infrastructure and networks, good access and entry conditions and sound structure for FDI. Finally, companies engaged in escape investments seek good access and entry conditions and a good institutional framework and structure for FDI (positive institutional distance and stability).

2.3 Sectoral foreign direct investment priorities

As aforementioned, foreign direct investment was severely impacted by the COVID-19 pandemic. Global FDI has experienced a decline of 42% in 2020, returning to the FDI flows level seen in 2005 (UNCTAD, 2021a). International investment flows are essential for recovery and sustainable development. Thus, investment plans focusing on strategic areas that drive development and structural change, such as energy, ICT and electronics, and financial services, are priorities for governments and the private sector. These three sectors are among the top ten industries in value terms related to announced greenfield projects in 2019–2020 (UNCTAD, 2021b).

Greenfield projects in energy and gas supply decreased in 2020 because of the pandemic impacts 13% to $99bn. However, foreign investors continue to invest, especially in renewable energy projects. The sector registered a record in value and number of announced greenfield projects in 2019 ($113bn/560 projects) and showed resilience. Project finance activity in renewable energy projects continued to grow, registering a growth rate of 7% in 2020. The ICT industry has experienced a growth of 22% in value because of the increased demand for digital infrastructure and services during the pandemic (UNCTAD, 2021b). Financial services are also relevant, especially FinTech's and online platforms that facilitate and democratize access to capital and credit. This industry has an indirect impact in other sectors as well, for instance, by investments in companies and industries with high sustainable development impact (Betti *et al.*, 2018; Eccles, 2019).

Specificities of each sector and distinctive motives to engage in FDI implies that different attractiveness factors may be relevant to international investors. One of the criticisms of indexing countries is the lack of product or area specificity in the indicators (Cavusgil *et al.*, 2004). Because of the importance of these industries to the Sustainable Development Goals (SDGs), such as ensuring access to affordable and clean energy, reducing inequality, promoting sustainable industrialization and fostering innovation (Betti *et al.*, 2018; George *et al.*, 2016) and to a faster recovery post-COVID-19, we propose specific attractiveness indexes to energy, ICT and financial services sectors.

3. Methodology

3.1 Data

The starting point in the elaboration of the composite index of FDI attractiveness is the identification of the relevant determinants of FDI. We followed the conceptual framework proposed by Bretas *et al.* (2021), which suggests five main sub-domains of FDI determinants:

(1) entry conditions;

(2) institutional framework;

(3) market conditions;

(4) resource offer; and

(5) structure for FDI.

According to the model, companies prioritize host markets offering good market conditions (market growth, size, trade flows, open trade regimes and regional integration), good access and entry conditions, good production conditions (low cost of production and labor, availability of natural resources), good institutional framework (governance and acceptable risk) and suitable structure for FDI (financial development, political stability, inflation, exchange and interest rates, taxes and capital regulation).

These factors were applied in numerous empirical studies confirming their impact on FDI (Asiedu, 2006; Asiedu and Lien, 2004; Du *et al.*, 2008; Wheeler and Mody, 1992). Each sub-determinant will contribute differently to aggregate composite indicator and country ranking. For example, a country like Finland could be very strong on entry conditions, whereas China could be strong on market conditions. The decomposition of the composite indicator can thus shed light on the overall performance of a given country. Tools like AML could help to further improve knowledge on the relationships between the composite and its components.

We rely on several databases with annual data ranging from 2006 to 2019. More precisely, the data is collected from the World Bank, UNCTAD, IMF and fDi Markets database. The selection of the main variables for each sub-determinant described above depends on the data availability to maximize our country sample. We finally selected 17 variables that exhibit a large country coverage for the period considered. We have included all countries with data available for each year in our final sample. Table 2 presents the dependent and independent variables selected, together with their description, acronym, source, means and standard deviations. To ensure comparability, we deflate some variables by GDP. Not all the variables are raw data but represent ready-made indexes, such as index product diversification index of exports or the commodity export price index. The advantage of using indexes is that they allow tracing back key drivers values in one variable to increase the level of detail.

As said before, the inclusion of a country in our index is driven by the availability of the data. The idea was to find an adequate representation of countries in all regions of the work

Table 2.
Variables

Variable	Sub-determinant	Acronym	Mean	SD	Source
Dependent variables					
Total FDI - capital expenditure		Total Capex	5961.672	12545.02	FDI Markets
Capital expenditure – energy		Energy Capex	1747.05	3963.306	FDI Markets
Capital expenditure – financial services		Financial Capex	362.4981	970.1598	FDI Markets
Capital expenditure – ICT		ICT Capex	868.6696	2047.652	FDI Markets
Foreign direct investment: inward flows, percentage of gross domestic product		FDI_inw_GDP_perc	6.798425	23.033	UNCTAD
Independent variables					
Control of corruption: rank	Institutional framework	Control_corruption_rank	50.047	29.061	World bank
Political stability and absence of violence/terrorism		Polit_stable_percentile	50.027	29.043	World bank
Rule of Law: percentile		Rule_law_rank	50.023	29.032	World bank
Index product diversification: index of imports	Market conditions	Imp_Diversification_index	0.441	0.123	UNCTAD
Index product diversification index of exports		Exp_Diversification_index	0.668	0.146	UNCTAD
GDP growth (annual %)		GDP_growth_WBDB	3.394	5.292	World bank
GDP per capita growth (annual %)		GDP_pc_growth_WBDB	1.973	5.132	World bank
Exports of goods and services (% of GDP)		Exp_perc_GDP	44.125	33.525	World bank
Imports of goods and services (% of GDP)		Imp_perc_GDP	50.664	31.356	World bank
Trade (% of GDP)	Entry conditions	Trade_open	94.789	61.681	World bank
Agricultural raw materials exports (% of merchandise exports)	Resources offer	Agric_exp_perc	3.371	7.498	World bank
Ores and metals exports (% of merchandise exports)		Metal_exp_perc	8.232	13.91	World bank
Total natural resources rents (% of GDP)		nat_res_pc_gdp	6.676	11.059	World bank
Commodity Export Price Index, Individual Commodities Weighted by Ratio of Exports to GDP		Exp_prices	98.251	4.726	IMF
Commodity Import Price Index, Individual Commodities Weighted by Ratio of Imports to GDP		Imp_prices	98.252	2.541	IMF
Inflation, GDP deflator (annual %)	Structure for FDI	Inflation_WBDB	5.326	8.983	World bank
Tariff rate, most favored nation, simple mean, all products (%)		Tariff_MFN	8.889	4.675	World bank

as well as in different development stages (advanced and emerging countries). Our data set covers 135 countries grouped into six different regions (Africa, Asia, North America, South America, Europe and Australia).

3.2 Index construction

The index construction methodology follows the approach of Nardo *et al.* (2008) and can be divided into three steps. In the first step, we apply factor analysis to group together variables to form composite indicators that capture common information among variables. In the second step, we aggregate indicators obtained to form an index of FDI attractiveness. The results obtained are sensitive to the techniques used for calculation. Therefore, we use different proposed methods and aggregation techniques to calculate different index versions. The explanatory power of the results of these indexes is further compared to detect which combination yields the best result and, therefore, an adequate indicator of FDI attractiveness. As a final step, we use AML to attribute weights to the resultant factors and generate the consolidated indexes (overall and per sector). AML provides a hierarchy of predictors by checking the significance of each variable (Doornenbal *et al.*, 2021; He *et al.*, 2021).

3.2.1 Factor analysis. EFA is a reduction technic that aims at removing redundancy or duplication from a set of correlated variables. EFA identifies the underlying data structure through a regression model able to link the manifest variables to a set of unobserved latent variables. Unlike the principal component analysis (PCA), the EFA tries to explain the covariances or correlations of the observed variables by means of a few common factors. Despite these main differences, the results arising from the two techniques are similar. In this research, we perform the EFA technique after having tested that it is the most suitable technique for our data set.

Factor analysis aims to describe a set of Q variables, v, v_2, v_3,.,v_q, with a smaller number of factors f and highlighting the relationship between these variables. Despite their similarities, the mathematics behind FA is different from PCA. The first assumes the existence of latent factors underlying the observed data, whereas instead PCA seeks to identify variables that are composites to the observed variables. In formula:

$$v_1 = \alpha_{11}f_1 + \alpha_{12}f_2 + \ldots + \alpha_{1q}f_q + \varepsilon_1$$

$$v_2 = \alpha_{21}f_1 + \alpha_{22}f_2 + \ldots + \alpha_{2q}f_q \ \ + \varepsilon_2$$

$$\ldots$$

$$v_q = \alpha_{q1}f_1 + \alpha_{q2}f_2 + \ldots + \alpha_{qq}f_q + \varepsilon_q$$

where v are the standardized variables with zero mean and unit variance; α are the factor loadings related to the variables; f are uncorrelated common factors with zero mean and unit variable, whereas ε are the specific factors supposed independently and identically distributed with zero mean.

The standard practice is to choose factors that:

- have associated eigenvalues larger than one;
- contribute individually to the explanation of overall variance by more than 10%; and
- contribute cumulatively to the explanation of the overall variance by more than 60% (Nardo *et al.*, 2008).

3.2.2 Automated machine learning. AML is an artificial intelligence class of models that minimizes predictive errors, explores patterns in the data and makes predictions based on these patterns through algorithmic learning. It finds the optimal solutions between a set of variables (predictors) and a target (in this case, FDI). AML enables big data exploration and validates theoretical patterns derived from the data based on abductive reasoning, contributing to phenomenon-based theorizing (Doornenbal *et al.*, 2021; von Krogh, 2018). A target variable (dependent variable) is selected, and suitable models are suggested through machine learning based on algorithms for accurate predictions (Larsen and Becker, 2021). AML handles missing cases in the dataset by conducting a series of quick tests and comparing the predictive power of several variables.

The process consists of three phases, data partitioning, training and hyperparameter tuning and model scoring. The data is partitioned into segments, known as training data, and uses learning algorithms to test and validate various models on other data segments. Then, AML identifies the models that perform well, with high predictive accuracy and robustness, across the different data partitions. Finally, AML provides a hierarchy of predictors by checking the significance of each variable through the process of perturbation. Random numbers are added to the independent variables to verify how they affect prediction accuracy. The variable is considered important if it impacts the prediction accuracy (Doornenbal *et al.*, 2021; He *et al.*, 2021).

As conventional modeling, we use a time-aware model to predict future events without assuming that the relationship between predictors and the target is constant over time. We implemented it by using out-of-time validation (OTV) date/time partitioning (Figure 1). OTV is used when data is time-relevant, and the goal is to predict the target value on each individual row (DataRobot, 2022).

Blueprints are used for modeling. The blueprints map inputs to predictions by coupling an AML model with a preprocessing step. In this study, we use 12 different models for process data related to the total FDI. The best model recommended for deployment is the random forest regressor using the algorithmic data preprocessor tree-based algorithm preprocessing, $v1$. Random forests are a "combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest" (Breiman, 1999, p.1). Random forest regressors fit individual decision trees to random re-samples of input data. These tree predictors reduce the bias of an individual tree, making the prediction more accurate.

For the three sectors, 12-time series models were investigated with different algorithmic data preprocessors. For the energy sector, the best-selected model is the Generalized Additive2 Model (Gamma Loss) and text fit on residuals (L2/Gamma Deviance). For ICT and electronics, the selected model is Light Gradient Boosting on ElasticNet Predictions (Gamma Loss) and Boosting Model Preprocessing v1. For financial services, the model chosen is eXtreme Gradient Boosted Trees Regressor (Gamma Loss) and Tree-based Algorithm

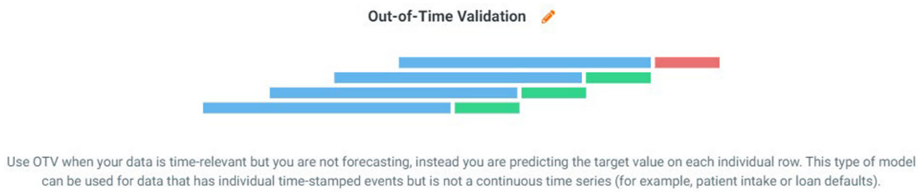


Figure 1.
Time-aware modeling

Preprocessing v1 (Barsotti *et al.*, 2021; Olsavszky *et al.*, 2020). Figure 2 shows the blueprints for general and sectoral analyses.

4. Results

The indicators capture different broad dimensions of the sub-determinants of FDI attractiveness (institutional framework, entry conditions, market conditions, resource offer and structure for FDI). Because these variables capture different dimensions, there is a strong likelihood that they would be highly correlated. Table 3 shows the matrix of pairwise correlation coefficients of the variables. As one can see, correlations between all pairs of variables are significant. Therefore, this study uses FA to reduce the dimension of the data set. We test the internal consistency – how closely related a set of items are as a group through – through the Cronbach's alpha measure. Results are in Table 4.

The resulting alpha coefficients in Column 5 of Table 4 are higher confirming that they have shared covariance and measure the same underlying concept [1].

4.1 Factor analysis results

In Figure 3, we plot the Eigenvalues after FA, whereas Table 5 depicts the factor analysis results.

The result of the estimation suggests that with four factors it is possible to explain a large part of the data variance (91.9%). The economic interpretation of this result is that the choice of the key drivers is appropriate for our purpose of measuring FDI attractiveness for the countries selected. This attractiveness can be measured through four single factors that represent the sub-determinants identified (institutional framework, market conditions, resources offer and structure for FDI). As a standard approach, we rotate the factors using the orthogonal varimax technique. The rotated factors maximize the variance of the squared loadings of a factor on all the variables in a factor matrix. The components loadings and the resulting weights from the rotated

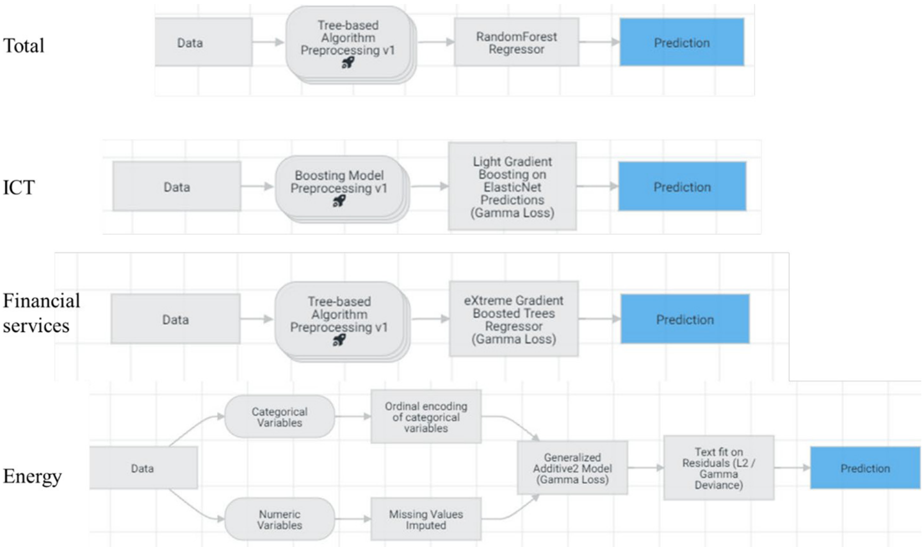


Figure 2.
Blueprints

Table 3.
Correlation matrix

	Control_ corruption_ rank	Polit_stab_ percentile	Rule_law_ percentile	Imp_ Diversification_ index	Exp_ Diversification_ index	GDP_ growth_ WBDB	GDP_pc_ growth_ WBDB	Exp_perc_ GDP	Imp_perc_ GDP
Control_corruption_rank	1								
Polit_stab_percentile	0.807***	1							
Rule_law_percentile	0.949***	0.807***	1						
Imp_Diversification_index	–0.567***	–0.329***	–0.558***	1					
Exp_Diversification_index	–0.519***	–0.318***	–0.566***	0.787***	1				
GDP_growth_WBDB	–0.158	–0.07	–0.176*	0.190*	0.214*	1			
GDP_pc_growth_WBDB	–0.124	–0.042	–0.107	–0.017	–0.021	0.695***	1		
Exp_perc_GDP	0.341***	0.408***	0.351***	–0.006	–0.146	0.092	0.029	1	
Imp_perc_GDP	0.237**	0.315***	0.265**	0.098	–0.131	0.042	0.108	0.872***	1
Trade_open	0.302***	0.376***	0.320***	0.044	–0.143	0.07	0.068	0.971***	0.964***
Exp_prices	0.11	0.083	0.167	–0.126	–0.217*	–0.184*	0.179*	–0.261**	0.013
Imp_prices	–0.019	–0.003	–0.047	–0.261**	–0.098	0.039	–0.007	–0.334***	–0.525***
Agric_exp_perc	–0.194*	–0.071	–0.226*	0.281**	0.190*	–0.053	–0.07	–0.178*	–0.11
Metal_exp_perc	–0.064	–0.036	–0.096	0.025	0.268**	0.109	0.141	–0.134	–0.119
nat_res_pc_gdp	–0.193*	–0.141	–0.241**	0.195*	0.392***	0.226*	–0.145	0.021	–0.278**
Inflation_WBDB	–0.339***	–0.275**	–0.364***	0.174	0.415***	0.239**	0.104	–0.103	–0.184*
Tariff_MFN	–0.392***	–0.371***	–0.382***	0.413***	0.328***	0.004	–0.055	–0.353***	–0.330***

	Trade_open	Exp_prices	Imp_prices	Agric_exp_perc	Metal_exp_perc	nat_res_pc_gdp	Inflation_WBDB	Tariff_MFN
Trade_open	1							
Exp_prices	–0.136	1						
Imp_prices	–0.438***	–0.022	1					
Agric_exp_perc	–0.151	0.067	0.037	1				
Metal_exp_perc	–0.131	0.215*	–0.025	–0.001	1			
nat_res_pc_gdp	–0.124	–0.778***	0.300***	0.001	0.076	1		
Inflation_WBDB	–0.146	–0.389***	0.113	0.015	0.193*	0.485***	1	
Tariff_MFN	–0.354***	0.098	–0.107	0.171	–0.022	0.067	0.037	1

Variable	(1) Sign	(2) Variable-test correlation	(3) Variable-rest correlation	(4) Av. inter-variable correlation	(5) Alpha
Control_corruption_rank	+	0.7742	0.7094	0.1584	0.7507
Polit_stab_percentile	+	0.6865	0.5983	0.165	0.7597
Rule_law_percentile	+	0.7991	0.7404	0.1565	0.748
Imp_Diversification_index	−	0.3947	0.176	0.1896	0.7892
Exp_Diversification_index	−	0.5781	0.4102	0.1711	0.7676
GDP_growth_WBDB	−	0.4198	0.2912	0.1868	0.7862
GDP_pc_growth_WBDB	−	0.3232	0.1869	0.1943	0.7942
Exp_perc_GDP	+	0.6352	0.5418	0.1708	0.7672
Imp_perc_GDP	+	0.5816	0.4772	0.1748	0.7722
Trade_open	+	0.6409	0.5481	0.1707	0.7671
Exp_prices	+	0.3032	0.0054	0.2021	0.8021
Imp_prices	−	0.3286	0.0465	0.1974	0.7974
Agric_exp_perc	−	0.3013	0.1674	0.1914	0.7911
Metal_exp_perc	−	0.2728	0.1338	0.1939	0.7937
nat_res_pc_gdp	−	0.5093	0.3951	0.1782	0.7762
Inflation_WBDB	−	0.3669	0.2401	0.1888	0.7884
Tariff_MFN	−	0.557	0.4468	0.1763	0.774
Test scale				0.1804	0.7891

Table 4. Cronbach's alpha test results

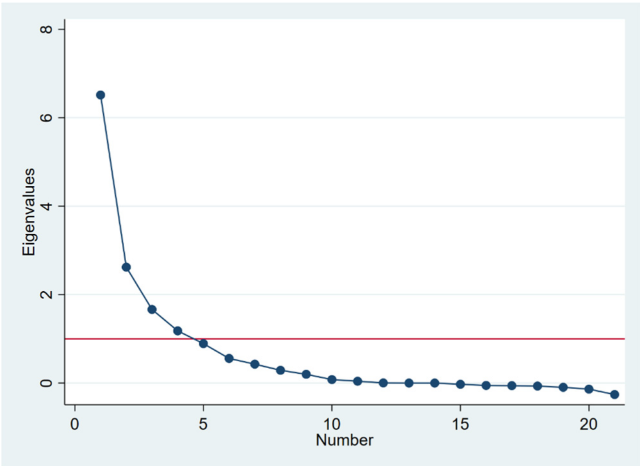


Figure 3. Screenplot of Eigenvalues after FA

components matrix are provided in Table 6. The table also allows to better visualize which variables represent each component loading.

The first latent factor has strong positive loadings with the institutional framework (control of corruption, political stability, rule of law), while it exhibits negative loadings with the variables related to: import and export diversification, agricultural exports and structure for FDI (inflation and tariff rate). The second factor has higher and positive loadings with three important market conditions related to openness for FDI attractiveness: exports in percentage of GDP, imports in percentage of GDP and import prices. The

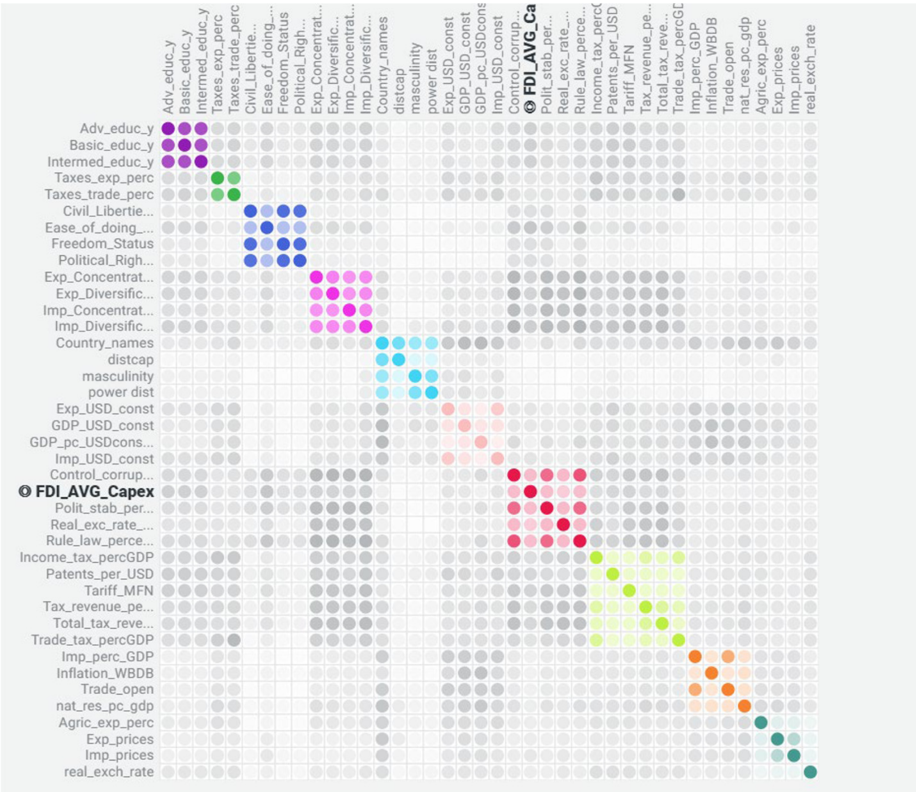


Figure 4.
Feature association matrix

Table 5.
FA Results

Factor	Eigenvalue	Unrotated (%) of variance	Cumulative	Rotated (orthogonal varimax) Eigenvalue	(%) of variance	Cumulative
Factor1	4.725	0.448	0.438	3.366	0.319	0.319
Factor2	2.468	0.234	0.683	3.249	0.308	0.628
Factor3	1.654	0.157	0.839	1.821	0.173	0.800
Factor4	0.834	0.079	0.919	1.244	0.118	0.919

third factor refers to economic growth in terms of GDP and GDP per capita growth. Finally, the fourth factor explains the remaining variables related to resource offer and structure for FDI.

For an easier interpretation of the factors in the remaining part of the document, we attach to their suffix for the determinants captured:

- Factor 1: Governance and Diversification;
- Factor 2: Protectionism;
- Factor 3: Economic Growth; and
- Factor 4: Natural Resource Endowment.

Variable	Factor1 governance and diversification	Factor2 protectionism	Factor3 economic growth	Factor4 natural resource endowment	Uniqueness
Control_corruption_rank	0.904				0.123
Polit_stab_percentile	0.742	0.3265			0.335
Rule_law_percentile	0.918				0.087
Imp_Diversification_index	−0.633			0.457	0.341
Exp_Diversification_index	−0.531			0.628	0.312
GDP_growth_WBDB			0.922		0.113
GDP_pc_growth_WBDB			0.931		0.117
Exp_perc_GDP		0.936			0.057
Imp_perc_GDP		0.984			0.019
Trade_open		0.983			0.006
Exp_prices				−0.353	0.836
Imp_prices			−0.235		0.931
Agric_exp_perc	−0.18				0.949
Metal_exp_perc				0.160	0.953
nat_res_pc_gdp				0.626	0.567
Inflation_WBDB	−0.263				0.892
Tariff_MFN	−0.477	−0.277			0.672

Table 6. FA rotated components matrix

After having obtained the factors, we can build a first ranking that captures FDI attractiveness. First, we normalize each factor on a point scale from 1 to 100 points percentage, where 100% represents the best score and 1% the worst. The normalization is obtained through the following linear transformation:

$$Factor_i = \frac{Factor_i - \min(Factor_i)}{\max(Factor_i) - \min(Factor_i)}$$

The normalization allows us to easily interpret each country performance in terms of: governance and diversification, protectionism, economic growth and natural resource endowment.

After that, we follow common practice, and we calculate a composite index of FDI attractiveness by weighting each factor based on the percentage of variance explained over the total variance explained using the rotated results. For example, governance and diversification factor (Factor 1) has a weight of 0.31 over 0.91.

In formula:

$$FDI\ \ attractiveness\ \ Index = \sum_{i=1}^{n=4} \frac{\%\ \ of\ \ variance\exp Factor_i}{Tot.\ variance\ \ exp} * Score_i \quad [4]$$

In Table 7, we report the country ranking created for the year 2019 [2] based on FA.

4.2 Automated machine learning results

Figure 4 shows the feature associations matrix, in which associations within the data can be visualized. The matrix illustrates the detected relationships between categorical and numerical information, the extent features (or variables) depend on each other and the

Table 7.
FA Index – top and bottom ten countries

Rank_FA	Country	Index_FA (%)
1	Luxembourg	69.25
2	Singapore	66.38
3	Ireland	61.25
4	China, Hong Kong SAR	61.09
5	Brunei Darussalam	59.62
6	Malta	57.73
7	United Arab Emirates (UAE)	57.24
8	Qatar	55.94
9	Switzerland	55.04
10	Netherlands	54.57
77	Ecuador	34.14
78	El Salvador	33.96
79	Madagascar	33.02
80	Egypt	33.00
81	Kenya	32.65
82	Kyrgyzstan	32.30
83	Pakistan	29.26
84	Nicaragua	28.75
85	Comoros	28.18
86	Burundi	25.97

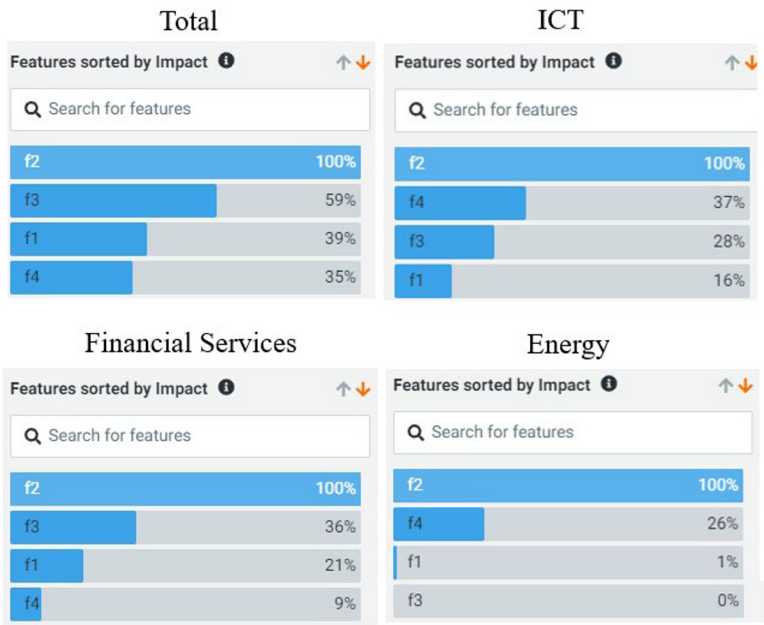
clusters, in which variables are partitioned based on their similarity, denoted by color. In the matrix, we can observe the strength and nature of the associations and detect families of pairwise association clusters. For instance, variables related to education form one cluster (purple), political freedom and democracy form another cluster (blue) and market-related variables are associated in the cluster in red.

Normalization tests are not required as AML normalizes the data and uses appropriate models to fit the data distribution. Figure 5 reveals the feature effects for total FDI and the three sectors analyzed, showing which features are the most important in each prediction model based on the perturbation process. The most important item is assigned 100%. Protectionism is the most relevant predictor in general and for the three sectors. In total FDI, protectionism is followed by economic growth, governance and diversification and natural resource endowment. To ICT, after protectionism, the most relevant factors are natural resource endowment, economic growth and governance and diversification. With regard to financial services, economic growth comes in second, then governance and diversification and natural resource endowment. To the energy sector, economic growth is not a relevant factor.

Figures 6 and 7 show the partial dependence (average partial dependence) of each factor related to total FDI and FDI in the three specific sectors. The curve illustrates the factor's marginal effect on the target variable and indicates if the relationship between the feature and target is linear, monotonic or complex. It is possible to observe how a change in the value of the factor while keeping all other factors the same impacts the model's predictions. The charts reveal non-linearities between target and factors analyzed.

4.3 Foreign direct investment attractiveness index

Table 8 reports the top and bottom ten countries at the FDI attractiveness overall ranking and the rankings for the three sectors (energy, ICT and financial services) for 2019 [3]. We recalculate the weights of each factor through a machine learning algorithm (AI). More



Notes: Governance and diversification/factor, 2. protectionism/factor, 3. economic growth/factor and 4. natural resource endowment

Figure 5.
Feature effects

precisely, the AI algorithm allows recalculating the weights by relating the four loadings with the amount of FDI investments in each country during the sample period considered. Weights are also provided to three specific sectors of FDI: financials, energy and ICT.

AML results show that the level of protectionism, or openness conditions to attract FDI, play a big role in investors' decision of where to invest. Countries that rank better offer good market conditions to investors. The top five countries with the highest overall attractiveness indexes are Luxembourg, China (Hong Kong), Singapore, Malta and Ireland. These countries appear as top five destinations in all sectoral indexes, except for Malta (it is in 21th position) and Hong Kong (it is in 12th position) in the financial services rank. In the bottom five are Brazil, Nicaragua, Burundi, Pakistan and Argentina.

Countries' positions do not change significantly in energy and ICT ranks, even though the most relevant factor for these sectors (after protectionism) is natural resources endowment, not economic growth as the overall and financial services rankings. The ranking of financial services shows different countries as most FDI attractive. Some of the countries best ranked in the overall index, named Malta, Seychelles and Vietnam, lose several positions in the rank of the financial services. Scandinavian countries Denmark, Norway and Finland appear among the top ten for financial services FDI, alongside The Netherlands and Australia [4].

5. Discussion

Despite a substantial body of literature on FDI attractiveness factors, it is fragmented and lacks a shared understanding of the relevant determinants affecting FDI location decisions.

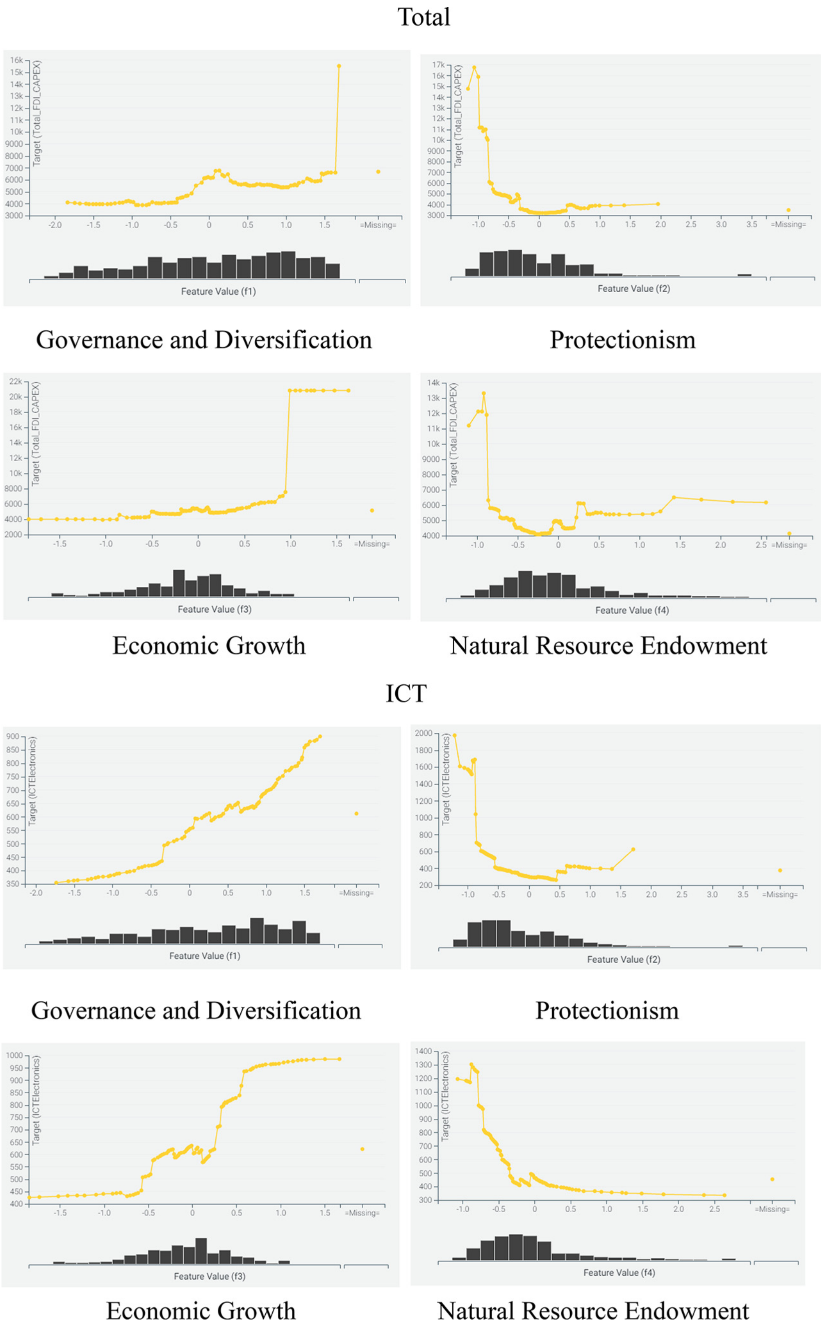


Figure 6.
AML results for total FDI and ICT

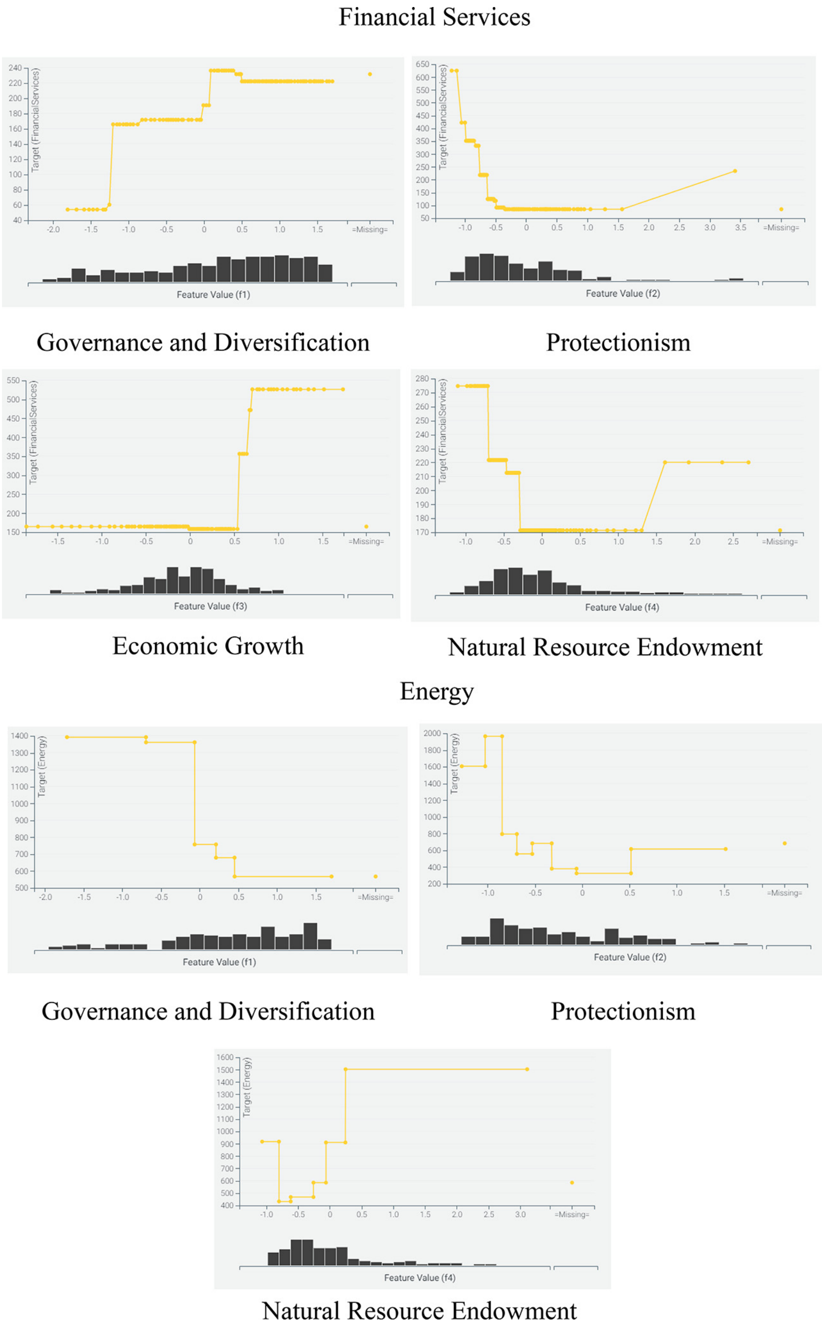


Figure 7.
AML results for financial services and energy

Table 8.
Country FDI attractiveness rankings – top and bottom ten countries

Rank	Country	Index – total (%)	Rank – financial services	Index – financial services (%)	Rank – energy	Index – energy (%)	Rank – ICT	Index – ICT (%)
1	Luxembourg	88.26	1	85.40	1	86.25	1	87.85
2	China, Hong Kong SAR	79.62	12	74.09	2	80.70	2	79.39
3	Singapore	79.54	2	83.39	3	72.74	3	76.12
4	Malta	76.94	21	71.37	4	65.95	4	72.08
5	Ireland	76.34	3	80.20	5	55.50	5	66.73
6	Vietnam	69.08	43	61.69	6	48.47	6	58.65
7	Seychelles	67.22	37	65.50	7	43.32	7	55.72
8	Brunei Darussalam	65.81	4	77.36	10	36.04	8	53.06
9	United Arab Emirates (UAE)	64.05	9	75.12	9	39.86	9	52.28
10	Slovakia	62.68	35	65.99	8	41.06	10	50.78
77	Italy	44.63	47	59.12	81	9.62	82	24.67
78	Ecuador	44.01	80	45.12	58	16.75	67	28.75
79	The USA	43.74	29	66.93	86	0.21	86	19.72
80	Comoros	43.23	84	36.51	60	16.51	68	28.20
81	Turkey	43.11	70	48.79	71	12.16	81	25.06
82	Brazil	42.31	64	50.29	84	7.69	84	22.99
83	Nicaragua	42.05	85	34.56	27	26.90	61	31.59
84	Burundi	41.93	86	32.62	54	17.35	69	27.80
85	Pakistan	40.87	83	39.41	72	11.90	83	24.35
86	Argentina	40.09	71	48.03	82	9.13	85	22.30

There have been few attempts to develop FDI attractiveness indexes, but the selection of factors is somewhat arbitrary and not based on theoretical foundations. Most of them are general and do not address the peculiarities of greenfield investment. Besides, limited linear and additive models are used. To overcome these deficiencies, we propose a comprehensive greenfield FDI attractiveness index, conceptually and methodologically robust.

The selection of factors in the previous indexes (Table 1) is not based on a solid theoretical foundation. For instance, the global foreign direct investment country attractiveness (GFICA) index (Jelili, 2020) uses only empirical literature on FDI to define the variables. The FDI attractiveness scoreboard (Copenhagen Economics, 2016) acknowledges Dunning's FDI motives classification. Still, the selection of the FDI drivers is determined based on the extent that policymakers can influence them and that can be integrated into their investment policies and strategies. The other indexes do not provide conceptual references.

Our index was constructed following a conceptual model that considers five main sub-domains of FDI attractiveness factors: entry conditions, institutional framework, market conditions, resources offer and structure for FDI (Bretas *et al.*, 2021). The model integrates seminal theoretical references (Dunning, 1998; Dunning and Lundan, 2008) and more recent developments in FDI research (Cuervo-Cazurra *et al.*, 2015; Cuervo-Cazurra and Narula, 2015), with a comprehensive review of the empirical literature. In that way, we provide a conceptually well-based index.

Regarding the methodology, two indexes used primary data with limited scope, the Kearney FDI Confidence Index and EY Attractiveness Survey, and the others adopted quantitative indicators. All of them used traditional linear models that assume a straight-line relationship between the dependent and independent variables. However, as one can observe in AML results (Figures 6 and 7), the relationships between the factors and FDI are not linear. For this reason, our index is also methodologically more adequate, as AML identifies non-linearities. It also suits better fields lacking a shared understanding of the exact predictors and their relationship with the target variables by using algorithmic learning.

Comparing our index results with other indexes makes it possible to observe the effects of weighting factors through a AI algorithm. By using linear models, previous indexes highlight aspects with a straightforward relationship with FDI inflows. GlobalEDGE uses the Delphi method with international business professionals and educators to attribute weights with potential subjectivities. Algorithmic learning attributed more importance to protectionism, or openness conditions for FDI, and economic growth in our overall index. Countries that usually do not figure between the top FDI attractive destinations have appeared well-ranked in our index, such as Vietnam, Seychelles, Brunei Darussalam and Slovakia. Thus, according to our results, countries should pay more attention to enabling adequate market conditions to attract FDI inflows. Moreover, investors might consider other nontraditional economies that present high-growth perspectives in their investment decisions.

Our results are aligned with UNCTAD's (2021b) analysis of FDI flows during the COVID-19 pandemic and prospects for recovery. The 2021 report highlights the relevance of investment hubs in Europe and East Asia among the largest FDI recipients globally, such as Luxembourg and Hong Kong, China. Moreover, developing Asia is the only region recording FDI growth during the pandemic. Our index shows five countries from developing Asia among the top ten attractive countries (China – Hong Kong, Singapore, Vietnam, Brunei Darussalam and United Arab Emirates). Besides, Ireland that ranked fifth in our total, energy, and ICT indexes and third in the financial services index, has developed an FDI-led growth model in the past years, becoming an important hub for Europe, the Middle East and Africa region, especially in the tech sector (Regan and Brazys, 2018).

In addition, we provide specific rankings to three strategic sectors, essential for post-pandemic recovery and sustainable development. Energy, ICT and electronics and financial services are priorities for governments and the private sector. Renewable energy greenfield projects are growing due to climate change challenges. For instance, Seychelles, seventh in the energy rank, had two large solar energy greenfield projects announced in 2020. The pandemic increased the demand for digital infrastructure and the values of greenfield FDI announcements in the ICT industry raised more than 22% (UNCTAD, 2021b). Based on our results, we observe that, after the level of protectionism, natural resource endowment is very important for both energy and ICT sectors. For financial services, economic growth is more relevant.

6. Conclusion

This article develops an FDI attractiveness index in a robust three-stage process. First, we identify the main critical variables based on a comprehensive conceptual model with five key sub-domains of FDI. After that, we run a factor analysis to reveal the most relevant features. Finally, we employed AML to recalculate the weights of the features, assessing the relative importance of each resultant factor in determining greenfield investments to generate the calibrated index.

Our article offers a valuable contribution as it overcomes the main limitations in the conceptualization and measurement of previous attempts to provide an FDI attractiveness index. It contributes to FDI research by offering a robust empirical measurement of location-choice factors identified in seminal theoretical references (Dunning, 1998; Dunning and Lundan, 2008) and more recent conceptual developments (Bretas *et al.*, 2021; Cuervo-Cazurra *et al.*, 2015; Cuervo-Cazurra and Narula, 2015) through a novel method, AML. Screening investment locations has been a challenge for investors. We provide a robust assessment tool for both practitioners and scholars to evaluate the countries' potential for greenfield investment.

FDI is critical for achieving economic growth, creating skilled jobs, enhancing innovation and development. The indices allow policymakers to identify gaps and policy priorities to attract foreign direct investments. They can use the overall and sectoral indexes to assess the areas in which policy actions might be necessary to overcome liabilities that prevent investments. Countries can develop and upgrade existing locational advantages by addressing factors identified in the study as critical to attracting FDI, such as openness conditions and economic growth. For instance, policies to promote economic integration by opening trade and capital flows and reducing tariff barriers impact economic growth and can attract more FDI inflows. In addition, we also present specific ratings for three strategic economic sectors, energy, ICT and electronics and financial services, in which investments are essential for a faster recovery post-COVID-19 and sustainable development.

Notes

1. Normal practice suggests a minimum alpha coefficient between 0.65 and 0.8. Alpha coefficients lower than 0.5 are usually not acceptable.
2. Country ranking is also available for the full sample of years 2006–2019 under request.
3. Country ranking is also available for the full sample of years 2006–2019 under request.
4. Country ranking is also available for the full sample of years 2006–2019 under request.

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