Foreign direct investment and local interpretable model-agnostic explanations: a rational framework for FDI decision making

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Abstract

Purpose – This study aims to examine foreign direct investment (FDI) factors and develops a rational framework for FDI inflow in Western European countries such as France, Germany, the Netherlands, Switzerland, Belgium and Austria.

Design/methodology/approach – Data for this study were collected from the World development indicators (WDI) database from 1995 to 2018. Factors such as economic growth, pollution, trade, domestic capital investment, gross value-added and the financial stability of the country that influence FDI decisions were selected through empirical literature. A framework was developed using interpretable machine learning (IML), decision trees and three-stage least squares simultaneous equation methods for FDI inflow in Western Europe.

Findings – The findings of this study show that there is a difference between the most important and trusted factors for FDI inflow. Additionally, this study shows that machine learning (ML) models can perform better than conventional linear regression models.

Research limitations/implications – This research has several limitations. Ideally, classification accuracies should be higher, and the current scope of this research is limited to examining the performance of FDI determinants within Western Europe.

Practical implications – Through this framework, the national government can understand how investors make their capital allocation decisions in their country. The framework developed in this study can help policymakers better understand the rationality of FDI inflows.

Originality/value – An IML framework has not been developed in prior studies to analyze FDI inflows. Additionally, the author demonstrates the applicability of the IML framework for estimating FDI inflows in Western Europe.

Keywords FDI, Machine learning, Interpretable machine learning, Local interpretable model-agnostic explanations

Paper type Research paper

1. Introduction

Foreign investment capital is important for the growth and development of both developing and developed economies (Nguyen, 2023). Therefore, foreign direct investment (FDI) inflow and its determinants have been discussed by various researchers in a wide range of contexts at the national, regional and firm levels (refer to Abu and Karim, 2016; Buckley *et al.*, 2012; Dinh *et al.*, 2019; Gheorghe and Marian, 2014; Nielsen *et al.*, 2017; Rahman and Shahbaz, 2013; Singh, 2023). Foreign investors' decisions on where to invest are based on various parameters

such as geopolitical, social, economic and geographical determinants, which lead to differences in FDI inflow strategies (Makojević *et al.*, 2016). Analyzing the FDI determinants, most researchers have focused on the traditional approach, and few have used the smartness learning approach to intelligence, networking, agility and other machine learning (ML) algorithms for a deeper analysis of the research problem. Furthermore, this smartness learning approach has limitations in terms of explainability, interpretability and trust because of human emotional interference. Driverless artificial intelligence (AI) enhanced transparency by presenting precise insights into the mechanisms and results of the generated model and its predictions, and the local interpretable model-agnostic explanation (LIME) enhanced trustworthiness by providing interpretability.

The ML algorithm is not new for determining the FDI attractiveness. Singh (2023) examined FDI inflow at the regional level in Hungarian counties using an artificial neural network (ANN) from 2001 to 2018 and found that the ANN can converge a wide variety of indicators that influence FDI inflow. The root-mean-square error (RMSE) value confirms that the ANN algorithm performs better than the general linear model (GLM) for determining FDI inflow. Meyliana *et al.* (2018) examined the factors that influence the foreign investment decisions at the country level, in the methodology, they implemented the classifiers such as a decision trees, support vector machine (SVM), gradient boosting machine (GBM), nearest neighbor, Gaussian processes, random forest (RF), neural network (NN), naive Bayes and adaptive boosting (ADA-boost) through ML algorithm. The results show that foreign companies benefit from the presence of overseas subsidiaries to minimize risk, and in all classifiers, the decision tree has the highest accuracy rate of 31.50%. Schneider (2020) identifies the factors affecting the FDI location selection decision process using a large dataset of 2361 variables from 217 countries and employs the RF regression model for feature selection and a deep neural network (DNN) to predict FDI values. The research uses hyper-tuning of parameters to select the hidden layers in DNN and RMSE benchmarks to measure the performance. The results suggest that the government should have slowly improved political and economic institutions by implementing continuous policy reforms, instead of relying on a few statically significant variables. A higher investment in the global community leads to international prosperity. Devereux and Griffith (2003) discuss the empirical literature on FDI inflows through a decision tree. In their literature review, they observed that the decision tree of FDI inflow literature can be classified into three groups. First, discrete choice examines the location of production or export units. Second, these studies used individual firm-level data to examine the determinants of FDI. Third, these studies use the confidential data of firms, mainly examining organizational sentiment for FDI.

A substantial amount of literature has explored different ML models to find the FDI determinants. Several studies have explored different statistical and ML models for determining FDI inflows. However, to the best of the author's knowledge, no prior study has developed an interpretable machine learning (IML) framework to determine FDI inflow decisions. Therefore, this study fills this gap and contributes to the literature by developing an FDI inflow decision framework utilizing the IML, or more specifically, the LIME. Additionally, the author demonstrates the applicability of the IML framework for estimating FDI inflows in Western Europe and contributes to rigorous science. This research applies three robust ML models through LIME using a driverless AI–H2O open-source platform to explore the FDI determinants. Several efforts were made in this study to accomplish the research goal. First, the author determines the FDI determinants and presents their global interpretation to understand their relationship with the prediction target. Second, since the most important variable of FDI is not the causation of actual FDI inflow, the author depicts the local interpretation through the LIME. Third, the FDI inflow decision tree is created based on the trusted variable found through the model-agnostic approach. Finally, we find causality among the variables using simultaneous equations. The objective of this study is to examine FDI factors and develop a rational framework to understand foreign investors' FDI inflow

decisions in Western European countries. Further, this study fills gaps in the literature by addressing the following question: First, how can ML-based prediction systems play an important role in investment decisions? Second, the model-agnostic IML approach and LIME can increase the trust level of foreign investors by creating ML reports. Third, the authors differentiate and identify the most influential and important variable for FDI inflow in the Western Europe (WE) region.

Further, this article propagates in the following sections: 2) a literature review presents possible covariates and the factors that are most important to investors, 3) data and descriptive statistics presented in this section, 4) the methodology sectio presents the econometrics behind the ML, 5) the results and discussion and 6) the conclusion section presents the limitation, policy implications and future recommendation.

2. Literature review
This section discusses and explores the possible factors related to FDI inflow. Numerous empirical and scientific articles discuss the determinants of FDI. The author focuses on a literature review of six factors: environmental pollution, trade, financial accumulation, gross value-added (GVA), economic growth and the country's national account financial stability.

2.1 FDI and environmental pollution
The empirical literature on FDI and environmental pollution can be classified into four categories. In the first category, it is evident that FDI reduces CO_2 emissions in the host country. Demena and Afesorgbor (2020) conducted FDI and environmental emissions meta-analyzes of 65 primary studies. The effect of FDI on the environment is almost zero; however, after heterogeneity, FDI reduces environmental emissions in developed countries compared with developing countries. This implies that FDI inflow standards in developed countries are high. Second, the category supports the "pollution haven hypothesis": FDI inflow significantly increases the CO_2 emission of the host country. Shao (2018) presents the relationship between FDI and environmental emissions using dynamic panel data and shows that FDI has a negative impact on carbon emissions in high-income, middle-income and low-income countries. However, after considering additional factors such as fossil fuels, trade openness, urbanization and industrial intensity, FDI has a positive impact on environmental emissions. The third category argues that the "pollution heaven hypothesis is insignificant practice" which means "pollution heaven" practices are not behavioral in the real world. Zhu et al. (2016) investigated FDI and CO_2 emission through quantile regression and concluded that FDI has an insignificant impact on low emission countries in low quantile and high emission countries have a positive impact; therefore, high emission countries pay more attention to environmental regulation and environmental problems. The fourth category supports both the "pollution halo" and "pollution-haven hypotheses. This means that FDI and CO_2 emissions have bidirectional causality when FDI causes emission, it supports the "halo hypothesis" and if emission cause FDI it supports the "pollution haven hypothesis". Shahbaz et al. (2018) analyze the environmental degradation effect by accounting for FDI, economic growth and financial development in France. This result supports the pollution haven hypothesis of FDI in France: FDI decreases environmental quality by increasing CO_2 emissions, while financial development decreases CO_2 emissions. Therefore, to achieve the European Union (EU) target of reducing domestic emissions by 40%, it is necessary to strengthen the financial sector. Doytch and Uctum (2016) analyze FDI and environmental effects along globalization and suggest that FDI inflow in services decreases pollution, supporting the halo hypothesis, while for the manufacturing sector, FDI inflow increases the pollution effect and supports the negative halo effect. FDI inflow in high-income countries

reduces the environmental pollution support halo effect, and in low- and middle-income countries, FDI inflows increase environmental pollution.

2.2 FDI and trade

Varamini and Kalash (2010) examined the role of FDI in trade balance and economic growth in European economies using the Granger causality test. This result suggests that economic growth has unidirectional causality with FDI inflow in emerging European economies, and there is no negative relationship between FDI and trade imbalance in European economies. Mitze *et al.* (2010) found a link between the German trade model and FDI in European countries, using a simultaneous equation model. Their findings suggest that West Germany and the EU15 have a positive impact on FDI inflows, imports and exports. Similarly, East Germany and the EU27 countries have a positive impact on FDI inflows, imports and exports. Similarly, East Germany and the EU27 countries have a positive impact between FDI inflow and, imports and exports. Nobi *et al.* (2020) examined the structural changes in the trade flow of different commodities using the hierarchical organization of the minimum spanning tree (MST). Their results show that manmade trade commodities are much more hierarchical than natural fuels such as minerals. Apostolov (2016) found a strong relationship between exports and FDI and between gross domestic product (GDP) and FDI in Southern Europe. Faeth (2006) tested the dynamic relationship between FDI, domestic investment, trade (imports and exports) and GDP. The results show that FDI directly enhances domestic investment and GDP, although GDP and FDI increase imports and decrease export growth. Furthermore, discounts in tax rates and lenient trade policies influence foreign investment decisions (Tian, 2018). The corporate tax has a significant effect on organisation for economic co-operation and development (OECD) countries from 2001 to 2013, where lower tax rates attract the FDI. Gropp and Kostial (2000) discussed the corporate tax in the sense of FDI flows and showed that net FDI inflow significantly affects the EU tax harmonization. They presented that countries, especially Germany, Italy and Ireland, slash their corporate tax rates as a result FDI inflow to these countries increased as well as the tax revenue also increased.

2.3 FDI and financial accumulation

According to Amighini *et al.* (2017), theories suggest that FDI plays an important role in financial development both indirectly through its impact on capital formation and directly as an external source of capital. Therefore, FDI and financial accumulation are positively associated. Argiro (2003) mentions that FDI inflow increases capital formation because it is a source of financing. Ruxanda and Murare (2010) find that FDI inflows increase gross fixed capital formation through spillover effects. Kalotay (2010) examined the FDI pattern in Europe and used gross fixed capital formation as a proxy for financial accumulation. In European regions, the ratio of FDI to fixed capital formation increases over time and is higher than the world average. Omri and Kahouli (2014) estimated the relationship between FDI, domestic capital and economic growth and concluded a unidirectional relationship between FDI and domestic capital formation and bidirectional causality between domestic capital and GDP. Finally, they concluded that FDI contributes to domestic capital growth, but the growth of domestic capital does not contribute to FDI inflow in the Middle East and North Africa region.

2.4 FDI and value-added

Sjöholm (2016) found that FDI and gross value added are associated with each other; foreign investment received from firms has a positive effect on value-added in a local firm and enhances the high level of value-added. Therefore, three main phenomena increase value-added. First, the foreign firm's resources bring management, technology and capital and

contribute to improving production. Second, the mechanism is based on the types of goods and services that are being produced in the host country. FDI might cause structural changes, such as the expansion from high-value-added manufacturing sectors to high-value service sectors. Third, technology spillover in the host country attracts foreign firms to invest in the host country and helps increase the expansion of local firms. FDI can impact value added through domestic firms. Similarly, the research by Alvarado *et al.* (2017) examines the impact of FDI on economic growth and uses the variables trade, physical capital, GVA in agriculture, GVA in service and GVA in the manufacturing sector. The results vary according to the development of countries: FDI has an insignificant effect in upper-middle-income countries, a negative and significant effect in lower-middle-income countries and a significant and positive effect on products in high-income countries. Adarov and Stehrer (2019) examine FDI, capital formation and structural change value chains in Europe. The results show that FDI constitutes an important driver of trade in value-added and global value chain participation. Furthermore, in terms of production, foreign-controlled companies and overall gross value added to the economy are related and improve economic growth (Domesová, 2011).

2.5 FDI and national account stability
Abu and Karim (2016) analyzed the relationships among economic growth, FDI, domestic investment and domestic savings in terms of a national account. The results demonstrate positive unidirectional causality from FDI to domestic investment and economic growth, and positive bidirectional causality between domestic investment and domestic savings. Similarly, Bayer (2014) finds a bidirectional relationship between FDI and gross domestic investment in the short run. Albulescu *et al.* (2010) found FDI determinants in Central and Eastern European regions. Their results show that the financial position of a nation not only supports investment sustainability but is also a significant determinant of FDI attractiveness. Overall, the stable financial position of a country plays an important role in attracting FDI. Mahmood *et al.* (2018) present that financial stability can be maintained by the optimal level of institutional development and attract more foreign investors. In the long-term, FDI and institutional stability are cointegrated and tend to move in the same direction. Thus, higher institutional stability attracts more FDI. Institutional stability is exogenous to FDI inflows, whereas FDI endogenously affects institutional stability.

Although substantial methods of FDI inflow have been estimated, the author finds a literature gap in a robust framework for FDI inflow based on rationality. This study contributes to the literature on FDI inflow estimations by developing an IML framework for FDI inflows. Further, the literature indicates that multiple sets of variables determine FDI inflow. Therefore, this study considered six factors in Western European countries: environmental, trade, economic growth, financial accumulation, GVA and national account stability. This study fills this gap in the literature by developing an FDI framework based on IML.

3. Method
3.1 Research design
In recent decades, high-dimensional data and complex variables have become common in business, economics and finance. Researchers have been using ML algorithms such as artificial, recurrent and convolution, regularization techniques (ridge, lasso and elastic net), and other ML classifiers to determine the FDI variables that can influence investors' investment decisions. Although the ML model has high accuracy and performance, it may discriminate against traits and characteristics to maximize the prediction accuracy (Molnar, 2019). Another drawback of ML methodologies is that they increase accuracy but are difficult for humans to interpret because of their "black-box" nature. According to a study by Ribeiro *et al.* (2016), IML

algorithms such as LIME have been developed to increase the interpretability of black-box models. Doshi-Vélez and Kim (2017) explain that the rigorous science of IML can be defined as the "ability to explain or to present in understandable terms to a human".

When it comes to predictive modeling instead of what is predicted? A good framework is "why a prediction was made. However, it reduces the predictive performance (Molnar, 2019). Therefore, it is important to emphasize trusted variables instead of important variables. Therefore, to find the most trusted variable for FDI inflow, the LIME algorithm was used. In contemporary LIME tests, what happens to the prediction when a variation of data feeds to the ML model and generates a new dataset of permuted samples? With this new dataset, LIME trains an interpretable model based on the weighted proximity of sampled instances to the instance of interest. ElShawi *et al.* (2019) found that the LIME outperforms in mimicking the black-box model and interpreting the model with accuracy and quality of explanation for tabular data.

Further, LIME helps to understand why ML model classifiers make FDI predictions and focuses on the training set of the local surrogate model instead of the global surrogate model. Contemporary LIME tests: what happens to the FDI inflow prediction when the variation of the dataset is fed to the ML models. To achieve this, LIME generates a new dataset of permuted samples. With this new dataset, LIME trains an interpretable model based on the weighted proximity of sampled instances to the instance of interest. The phenomena of LIME can be understood by the following steps: 1) permutation in LIME means replication of data, 2) similarity distance measure between original and permuted data, 3) generation of models for outcome prediction, 4) description of the outcome and selection of features, 5) model fit in permuted data based on the similarity score, and 6) depicting or generating a report based on feature weight. The FDI inflow estimation algorithm for Western European countries can be classified into two parts: the objects and the second explainer. Where the object consists of the FDI feature training data. To create FDI models, interpretable algorithms use the explainer-object, a type of feature distribution list of the training dataset, and ML models. The predictive model's algorithm is given on the GitHub University of Cincinnati, and the interested reader can find the details on (http://uc-r.github.io/lime). Figure 1 shows the framework of the FDI analysis.

Figure 1 depicts the FDI inflow decision-making framework. Methodologically, this research has three main components: open-source H2O, LIME, decision tree implemented through the ML algorithm and statistical component (simultaneous equation models).
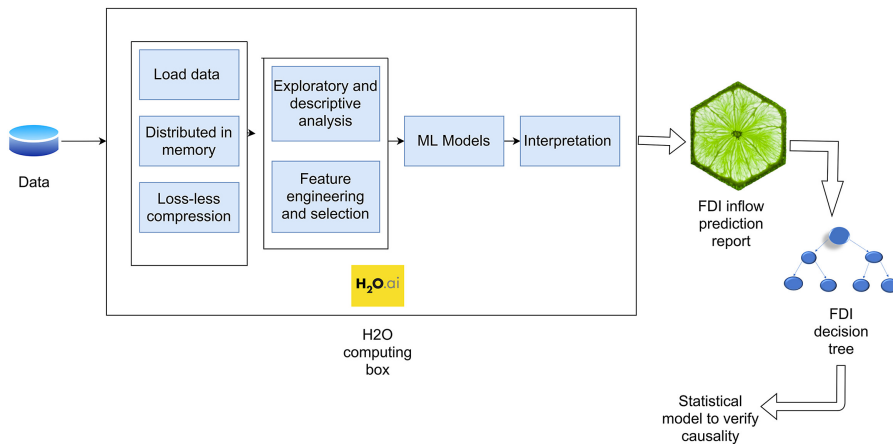
Figure 1.
Framework for FDI
analysis

Source(s): Own elaboration

The FDI inflow framework in this study is based on five steps. First, data were collected from the WDI database. The second step finds the most important determinant and presents an individual conditional expectation (ICE) plot to analyze how these variable observations impacted FDI inflow over time in Western Europe. In the third step, the author analyzed the FDI determinants through GLM, GBM and RF regression, forwarded this model to LIME and generated predictive reports. After describing the FDI inflow factors through the IML. Fourth, to understand how the FDI variable is involved in the FDI decision process, the author created a decision tree using Rpart based on the Gini impurity measure split nodes. A decision tree is useful for classifying variables in terms of the possible paths, nodes and branches. Within a decision tree, a branch leads to a possible path to follow, and a node represents the attribute of the variables. The drawback of ML is that it struggles to find causality among variables. Therefore, at this stage of the framework, there is a shortcoming because the decision tree and predictive model do not explain the causal relationship among the variables. To overcome this shortcoming, simultaneous equation models were used.

Therefore, to investigate how causality among these variables affects each other in the selected period, the author uses the three-stage least squares (3SLS) simultaneous equation approach to find causation among the variables. Therefore, in the fifth step, after presenting the most influential variable involved in the decision of FDI inflow in Western Europe, the author finds the causality among the variables involved in FDI inflow decisions through 3SLS simultaneous equation models. Thus, 3SLS has been used because of its advantages in that it makes it possible to estimate all the parameters of the model at the same time and consider a probable correlation between the error terms of the structural form of the model, which makes it more robust than other simultaneous techniques.

3.2 Data and variables

The data for this study were collected from the world development indicators (WDI) database from 1995 to 2018. Factors such as economic growth, environmental pollution, trade, domestic capital investment, GVA and financial stability of the country were selected through empirical literature. To model these factors, we used proxy variables such as economic growth as a proxy for real GDP. The other proxies for the variables are presented in Table 1 and the definitions of the variables are based on the WDI database. The variables used in this study and their details are listed in Table 1. Because the main merit of LIME is to predict the trusted model related to the real practical world, instead of predicting the log value that is not behavioral with the real-world prediction system because log normalizes the time effect, this research predicts the actual value, which is more accurately related to the practical world. However, to solve the variable's high range problem, the author converted the all-variable observation to the current United States (US) $/million and identified the causality author using a log.

Descriptive statistics and ranges of the variables are shown in Table 2. The descriptive table shows the mean, median, maximum values and quadrant values. The aggregative tendencies of the observations are shown as the means. The quartiles in the descriptive statistics represent the location of an ordered dataset. The first and third quartiles show the data set in 25 percentile (dataset of lower 25%) and 75 percentiles (dataset of lower 75%).

3.3 Analytical procedures

The methodology used in this research can be expressed by the following econometric expressions.

3.3.1 General linear model (GLM).

$$g(EY(y|x)) = \beta 0 + \beta 1x1 + \ldots \beta_p x_p \tag{1}$$

Dimensions	Literature support	Symbol	Variable definition
Foreign direct investment, inward	Dependent variable	FDII	Net inflows
Environmental	Shahbaz et al. (2018), Shao (2018), Demena and Afesorgbor (2020)	CO2	Adjusted savings: carbon dioxide damage
		PED	Adjusted savings: particulate emission damage
Trade	Cassou (1997), Mitze et al. (2010), Varamini and Kalash (2010)	EGS	Exports of goods and services
		IGS	Imports of goods and services
		EBGS	External balance on goods and services
		Tax	Taxes less subsidies on products
Economic growth	Almfraji and Almsafir (2014)	GDP	Gross domestic product
Financial accumulation	Faeth (2006), Kalotay (2010), Adhikary (2011)	GFCF	Gross fixed capital formation
		GNE	Gross national expenditure
		CFC	Consumption of fixed capital
		FCE	Final consumption expenditure
		GCF	Gross capital formation
Gross value added	Domesová (2011), Alvarado et al. (2017), Adarov and Stehrer (2019)	GVAM	Manufacturing, value added
		AGVA	Agriculture, forestry and fishing, value-added
		GVABP	Gross value added (GVA) at basic prices
		GVAC	Industry (including construction), value-added
National account financial stability	Albulescu et al. (2010), Abu and Karim (2016), Mahmood et al. (2018)	TR	Total reserves (includes gold)
		GDS	Gross domestic savings
		CI	Changes and stock of inventories held by firms

Note(s): All variables in current US$/million, data source: WDI
Source(s): Own elaboration

Table 1.
Variable description

The basic mathematical expression of GLM is given as (Molnar, 2019). Where basically, the GLM consists of components: g = link function, E_Y = distribution from the exponential family.

3.3.2 Random forest (RF). RF is based on the principal Gini index and entropy. The decision tree can be explained by the following equations (Gaber and Atwal, 2013):

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2 \qquad (2)$$

Where c = number of classes and Pi = relative frequency of the class.

Entropy determines how the node should branch the forest:

$$entropy = \sum_{i=1}^{C} -p_i * log_2(p_i) \qquad (3)$$

RF uses the distance of each node from the predicted actual value.

	FDII	GVABP	Tax	GDS	TR	GFCF
Min	−361467	175.626	20,983	52,966	11,828	48,933
1st Qu	14,241	384,959	45,719	118,308	23,239	97,102
Median	38,889	1,034,592	119,382	308,490	54,693	246,632
Mean	59,439	1,319,899	149,823	358,514	72,534	314,981
3rd Qu	73,038	2,275,612	258,815	552,619	112,600	540,060
Max	733,827	3,571,700	392,063	1,099,080	248,856	837,596

	EGS	CI	FCE	IGS	CO$_2$	GVAM
Min	78,792	−24161	143,834	80,519	689.9	35,847
1st Qu	259,640	1377	314,599	237,188	2150	64,046
Median	424,220	4818	846,636	417,765	4683.5	150,875
Mean	559,869	7793	1,111,209	524,124	6381	218,740
3rd Qu	740,120	13,334	1,932,183	742,031	8826.2	279,788
Max	1,877,740	47,344	2,864,690	1,634,020	25,455.6	795,960

	CFC	PED	GVAC	GCF	AGVA	GDP
Min	31,969	124.3	55,664	49,652	2624	196,800
1st Qu	72,063	268.5	99,986	101,352	4553	431,190
Median	180,632	671.9	246,062	247,156	17,166	1,155,124
Mean	251,921	950	327,618	322,774	20,503	1,469,723
3rd Qu	440,552	1308	482,781	558,743	35,192	2,519,378
Max	718,884	3153.4	1,085,110	855,359	47,221	3,963,770

Source(s): Own elaboration

Table 2.
Descriptive statistics

$$MSE = 1/N \sum_{i=1}^{N} (fi - yi)^2 \qquad (4)$$

Where: N = number of data points, fi = value returned by the model, yi = actual value at data point i.

3.3.3 Gradient boosting machine (GBM). The formulation of GBM is according to (Friedman, 2001; Natekin and Knoll, 2013).

$$(\rho t, \theta t) = \underset{\rho, \theta}{\text{argmin}} \left(-gt(xi) + \rho h(xi, \theta)^2 \right) \qquad (5)$$

Where, ρ = step size at tth iteration, $-gt(x)$ = boost increment in the function space, h(x, θ) = base-learner function or new function parallel to the negative gradient, i = 1 along the observed data, θ = parameter estimates.

3.3.4 Feature importance. Partial dependence plots (PDP) is the better tool to see the feature importance inside the model. The PDP for regression is expressed according to (Molnar, 2019; Das and Tsapakis, 2020):

$$\widehat{f}_{xS}(x_S) = E_{xc}\left[\widehat{f}(x_S, x_C)\right] = \int \widehat{f}(x_S, x_C)dP(x_C) \qquad (6)$$

X_S = one or two features of interest and X_C = other features used in the ML model $\widehat{f}$; X_S and X_c combined the whole features in the ML model.

3.3.5 LIME. Mathematically, the interpretability constraint can be expressed as follows:

$$explanation(x) = \underset{g \in G}{\text{argmin}} L(f, g, \pi_x) + \Omega(g) \qquad (7)$$

In an equation, x is the model g to minimize the loss function while the model complexity $\Omega(g)$ keeps low. π_x defines the neighborhood size around the instances x.

This article uses the three classifiers GBM, RF and GLM. All three models were built with an open-source ML platform H2O. The performance of the models was measured by the accuracy parameters such as RMSE and mean absolute error (MAE) etc.

3.3.6 Simultaneous equation model. To estimate the causality among foreign direct investmen inflow (FDII), gross value added construction (GVAC), particulate emission damage (PED) and exports of goods and services (EGS) were estimated through the following equation:

$$FDII_i = f\left(GVAC_i, PED_i, EGS_{i,}\right) \qquad (8)$$

where i = 1 . . . . . .N, country.

Write the equation in panel form and take the logarithm to attain reliable and consistent results. Further express the equation in a system of equation form as

$$\ln(\text{FDII})_{it} = \beta_0 + \beta_1 \ln(\text{GVAC})_{it} + \beta_2 \ln(\text{PED})_{it} + \beta_3 \ln(\text{EGS})_{it} + \varepsilon_{it} \qquad (9)$$

$$\ln(\text{GVAC})_{it} = \beta_0 + \beta_1 \ln(\text{FDII})_{it} + \beta_2 \ln(\text{PED})_{it} + \beta_3 \ln(\text{EGS})_{it} + \varepsilon_{it} \qquad (10)$$

$$\ln(\text{PED})_{it} = \beta_0 + \beta_1 \ln(\text{FDII})_{it} + \beta_2 \ln(\text{GVAC})_{it} + \beta_3 \ln(\text{EGS})_{it} + \varepsilon_{it} \qquad (11)$$

$$\ln(\text{EGS})_{it} = \beta_0 + \beta_1 \ln(\text{FDII})_{it} + \beta_2 \ln(\text{GVAC})_{it} + \beta_3 \ln(\text{PED})_{it} + \varepsilon_{it} \qquad (12)$$

Where the subscript in equations (9) to (12), i = 1, ..., N denoted country and t = 1, ..., T is the time period and ε is the error term.

108

4. Results

The author used an RF plot to identify the most important variables affecting FDI inflow in Western Europe. To further understand how the response variable FDI inflow changes according to these identified variables, we used the ICE plot. Because both RF and ICE depict global interpretation, the author uses LIME to develop the local interpretation model. Figure 2 depicts only the ten most important variables for FDI inflow, and Figure 3 depicts how the tax variable changes across observations.

ranger: RF_full
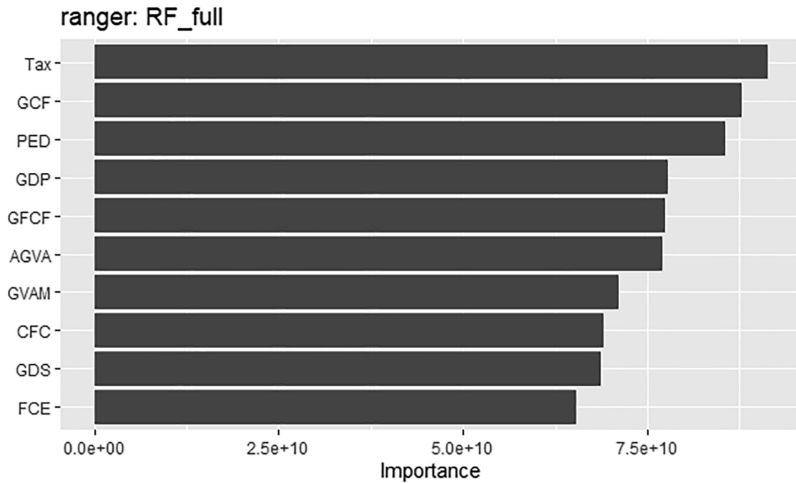
Figure 2.
Variable importance

Note(s): RF regression visualization only for the top 10 most important variables
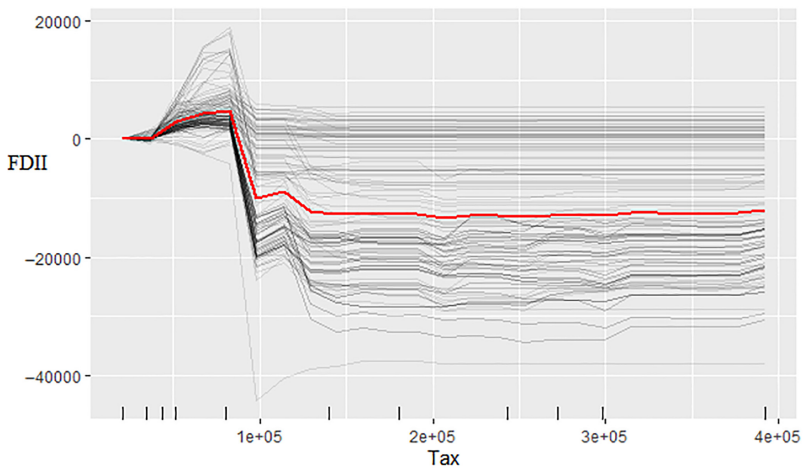**Source(s):** Own elaboration

Figure 3.
ICE plot to predict FDI inflow probability by the tax

Note(s): FDII: foreign direct investment inward
Source(s): Own elaboration

Figure 2 shows the magnitude of the variables that are most important for FDI inflow in Western Europe. The first point that emerges from Figure 2 is that tax subsidies on products are the most important variables for FDI inflow. The tax variable in this research indicates government subsidies on the current account of enterprises and subsidies on net taxes on products. According to Darby *et al.* (2014), industrial activity grows fruitfully in regions where the government provides tax subsidies. According to Tian (2018), the government should adopt tax subsidy strategies to attract FDI, where firms are in a position of high risk and high return. Furthermore, according to Abdioglu *et al.* (2016), net FDI inflows and taxes have country-specific effects because the purpose of scaling the tax rate is to lure FDI to accomplish the country's economic goal. Furthermore, gross capital formation (GCF) and gross fixed capital formation (GFCF) are the second and fifth most important variables, respectively. This indicates that the capital formation in Western Europe is positively associated with FDI inflow. For example, FDI inflow in the United Kingdom (UK) represented around one-third of the GFCF in 2006, but it varied according to year. The UK outperformed FDI inflow as a percentage of the GFC (Munday *et al.*, 2009).

The major drawback of the RF plot representation is that it does not indicate a relationship with the dependent variable. The RF plot indicates the importance of the independent variable with respect to that of the dependent variable. Therefore, to further examine how each instance of FDI inflow is associated with independent features, the author uses an ICE plot. Since it is difficult to present the ICE plot for all 10 variables in a single manuscript, the author presented the highly weightage variable only, i.e, tax. The ICE plot for taxes is shown in Figure 3.

Figure 3 shows how the FDI prediction for each instance is associated with the featured tax. Initially, the FDI inflow probability increased. Therefore, there is a positive relationship between the FDI prediction value and taxes. According to Agostini *et al.* (2007), subsidies on product tax rebates increase FDI inflows in European regions, such as Switzerland, Belgium, Austria and the Netherlands. The positive and negative relationships between corporate tax and FDI are similar to those in previous studies Gropp and Kostial (2000) and Cassou (1997). Once the tax value reaches a certain level, the FDI inflow decreases drastically and propagates almost in parallel for each instance. This means that increases in taxes decrease FDI inflows, implying a negative relationship (similar to Gropp and Kostial, 2000; Sato, 2012; Mudenda, 2015; Abdioglu *et al.*, 2016).

Three models, RF, GLM and GBM, were created, and the accuracy of their model performance is presented in Table 3. An explanation of this classifier is provided in the Figure A1. Continuous variables were split into 5 bins (cases). The low value of the RMSE in Table 3 shows the benchmarking sheet of model performance, and the lowest RMSE value indicates that the model has better accuracy. In this study, the best-fit ML model was GBM compared to other ML models and had the lowest RMSE value of 39,584.66.

Although the ML model has high accuracy, it is less trustworthy in the real world because of its interpretability. Furthermore, a single matrix with such classification accuracy is not trustworthy because of its incomplete explanation of real-world scenarios (Doshi-Vélez and Kim, 2017). Figure 4 shows the LIME report generated directly through the ranger RF. The other prediction models and their performances are presented in the Figure A1.

	GLM	RF	GBM
MSE	9,803,375,237	8,713,714,626	1,566,945,110
RMSE	99,012	93,347.28	39,584.66
MAE	56,611.78	41,274.26	17,093.42

Source(s): Own elaboration

Table 3.
Model performance
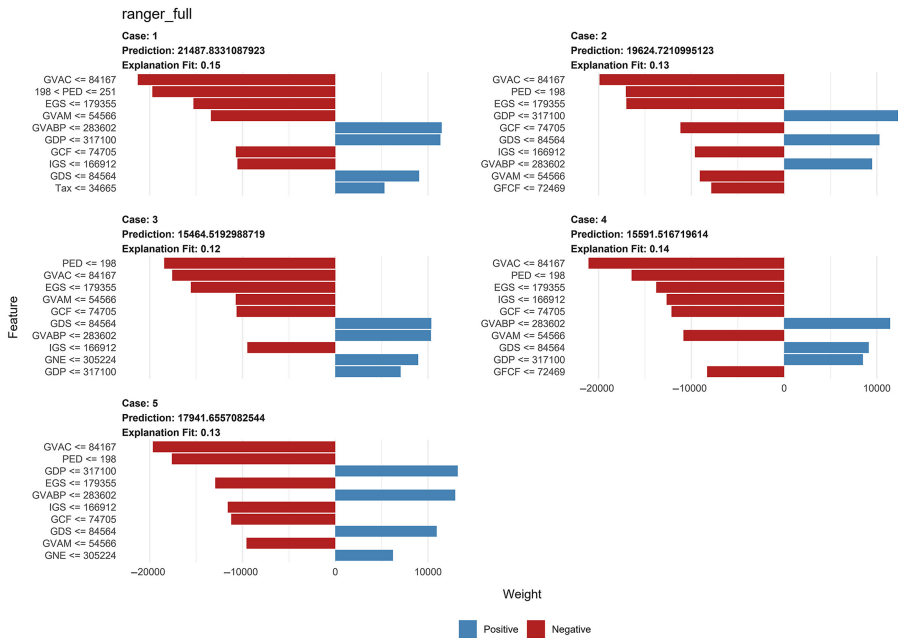
Figure 4.
LIME report of FDI
inflow

Note(s): Presentation only for ten most influential features
Source(s): Own elaboration

Figure 4 depicts the most trusted variables in the LIME report. Figure 4: Case 1 has the highest explanatory fit. From all the cases in Figure 4, GVAC is the most influential factor for FDI inflow in Western Europe. Trade factor variables such as EGS, IGS and tax; environmental factor variables such as PED; economic growth factor variables such as real GDP; domestic capital investment factors such as GCF and GFCF; GVA factor variables such as GVAC and gross value added manufacturing (GVAM); and financial stability factor variables such as total reserves (TR) are included in the ten most influential variables. Thus, all six factors are valuable for FDI inflows in Western Europe. These results are similar to those of Wojciechowski (2016), who found a long-term relationship between FDI and gross value added. According to Martínez-Galán and Fontoura (2019), after controlling the other FDI variables, the country's gross value added contributes positively to FDI inflow. Similarly, Abdouli and Hammami (2020) suggest that financial and economic policies should focus on protecting the environment along with economic growth, with a better level of financial development and FDI inflow. Sastre and Recuero (2019) suggested that the relationship between domestic investment and FDI depends on the type of industry and has a high forward integration with the global value chain. According to Faeth (2006) FDI, economic growth and domestic investment directly influence each other; however, they indirectly influence the trade variables.

Further, after finding the trusted variables, the author visualizes the variable through a decision tree to understand the transparent decision-making process of FDI inflow. In the decision tree algorithm, the author used an 80% training set and a 20% testing set. Figure 5 The first node from the top is the root node showing the mean FDI inflow in Western Europe. Each node in the decision tree shows the predicted value and percentage of observations. From Figure 5, it is evident that GVAC plays a more important role than PED, EGS, GCF and EGS in
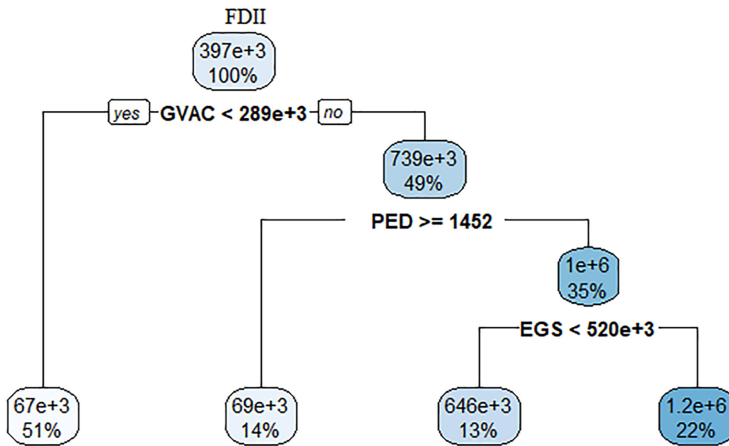
Note(s): Decision tree of FDI investment based on features selected through
LIME report
Source(s): Own elaboration

determining FDI decisions because it shows a direct effect. Countries that have been less than
the 289e+3 GVAC value tend to decide on an FDI inflow of 51%. According to Ciccone (2002)
gross value added is an important factor in the agglomeration of industries in France, Italy,
Germany, Spain and the UK. Mitze *et al.* (2010) found that agglomeration forces positively affect
FDI activity in Germany. Furthermore, PED and EGS also play important roles in FDI inflow
decisions. Therefore, if PED $\geq$1452 directly leads to FDI inflow with evidence of 14%
observation in the leaf of the decision tree, and if PED $\leq$1452, the decision of FDI inflow tends to
the EGS. This means that foreign investors are influenced by environmental regulations, which
further affect exports in Western European economies, such as Germany (Kordalska and
Olczyk, 2019). The environmental impact on FDI depends on the host country's domestic and
foreign firms' technology gap, capital endowment and environmental regulations in France,
Germany, Sweden and the UK (Zugravu-Soilita, 2017). Environmental policy affects the cost of
production and export-oriented FDI. Further, the export-oriented FDI is sensitive to
environmental regulation and then to local-market-orientated FDI; similarly, this is
observable in Figure 5 decision tree in reverse order (Tang, 2015).

5. Discussion
For continuous FDI inflow, a robust framework is necessary for formulating the policies. This
study developed a framework of FDI inflow and utilized the IML to interpret FDI inflow
factors and predictive performances, a decision tree to understand the involvement of
determinants in FDI inflow, and a simultaneous equation to determine causality. The author
used three ML models, GBM, GLM and RF, to find determinants of FDI, used these
determinants in LIME, and generated predictive reports. Finally, the author empirically
tested the relationship between FDI, PED, EGS and GVAC based on the variables involved in
the FDI decision tree. The performance of the models is presented in Table 4, where lower
RMSE and high R^2 values represent a better model. Overall, the results indicate that PED,
EGS and GVAC are the most trusted predictors of FDI inflow. Table 5 presents the model
estimated using the simultaneous equation. Three cases of causality exist among the
variables from FDI inflow to PED, GVAC and EGC.

	Austria				Belgium				France			
	R^2	RMSE	χ^2	p	R^2	RMSE	χ^2	p	R^2	RMSE	χ^2	p
FDII	0.20	0.055	9.72	0.02	0.12	0.124	15.72	0.00	0.20	0.044	9.60	0.04
PED	0.86	0.073	297.92	0.00	0.95	0.95	782.47	0.00	0.95	0.044	766.41	0.00
EGC	0.91	0.074	1553.33	0.00	0.93	0.93	474.72	0.00	0.88	0.108	228.46	0.00
GVAC	0.92	0.035	2719.16	0.00	0.95	0.98	1916.43	0.00	0.92	0.310	1380.41	0.00

	Germany				Netherland				Switzerland			
	R^2	RMSE	χ^2	p	R^2	RMSE	χ^2	p	R^2	RMSE	χ^2	p
FDII	0.18	0.097	13.16	0.00	0.20	0.565	14.00	0.00	0.20	0.044	6.99	0.04
PED	0.94	0.040	729.18	0.00	0.91	0.039	807.23	0.00	0.90	0.044	766.41	0.00
EGC	0.92	0.128	434.47	0.00	0.84	0.161	156.56	0.00	0.88	0.108	228.46	0.00
GVAC	0.95	0.033	1805.15	0.00	0.91	0.041	1193.71	0.00	0.91	0.031	1380.41	0.00

Note(s): $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$
Source(s): Own elaboration

Table 4.
3SLS model
performance and
equation summary
statistics

	Model 1 Austria	Model 2 Belgium	Model 3 France	Model 4 Germany	Model 5 Netherland	Model 6 Switzerland
logFDII						
logPED	−0.423**	1.816***	−0.454*	−1.039*	−7.332**	−0.454*
	(−2.90)	(3.54)	(−2.34)	(−2.26)	(−2.81)	(−2.34)
logEGS	−0.423**	0.185	−0.00767	0.0419	−1.725**	−0.00767
	(−2.90)	(0.74)	(−0.10)	(0.28)	(−2.69)	(−0.10)
logGVAC	0.946**	−2.031*	0.527	0.682	8.890***	0.527
	(2.99)	(−2.43)	(1.85)	(1.19)	(3.59)	(1.85)
cons	9.407***	23.62***	9.461***	11.34***	−24.33*	9.461***
	(7.29)	(5.54)	(5.58)	(4.17)	(−2.19)	(5.58)
logPED						
logFDII	−0.700**	0.212***	−0.441*	−0.167*	−0.0368**	−0.441*
	(−2.90)	(3.54)	(−2.34)	(−2.26)	(−2.81)	(−2.34)
logEGS	−0.927***	−0.298***	−0.206***	−0.247***	−0.0731	−0.206***
	(−9.24)	(−5.40)	(−3.61)	(−7.02)	(−1.95)	(−3.61)
logGVAC	2.099***	1.442***	1.365***	1.162***	0.925***	1.365***
	(12.92)	(15.17)	(16.05)	(17.73)	(15.92)	(16.05)
cons	1.444*	−9.819***	−2.204*	−2.342*	−3.341***	−2.204*
	(0.46)	(−11.15)	(−0.89)	(−2.01)	(−9.04)	(−0.89)
logEGS						
logFDII	−0.700**	0.114	−0.0472	0.0716	−0.146**	−0.0472
	(−2.90)	(0.74)	(−0.10)	(0.28)	(−2.69)	(−0.10)
logPED	−0.929***	−1.570***	−1.303***	−2.632***	−1.234	−1.303***
	(−9.24)	(−5.40)	(−3.61)	(−7.02)	(−1.95)	(−3.61)
logGVAC	2.166***	3.166***	2.839***	3.683***	2.539***	2.839***
	(30.21)	(11.53)	(7.38)	(13.40)	(4.92)	(7.38)
cons	1.199*	−16.14***	−13.71*	−16.47***	−7.473**	−13.71*
	(0.38)	(−5.53)	(−2.17)	(−4.85)	(−3.06)	(−2.17)
logGVAC						
logFDII	0.330**	−0.100*	0.243	0.0752	0.0453***	0.243
	(2.99)	(−2.43)	(1.85)	(1.19)	(3.59)	(1.85)
logPED	0.443***	0.609***	0.648***	0.799***	0.941***	0.648***
	(12.92)	(15.17)	(16.05)	(17.73)	(15.92)	(16.05)
logEGS	0.456***	0.254***	0.213***	0.238***	0.153***	0.213***
	(30.21)	(11.53)	(7.38)	(13.40)	(4.92)	(7.38)
cons	−0.655*	6.077***	2.413	3.035***	3.436***	2.413
	(−0.46)	(10.70)	(1.44)	(3.40)	(12.05)	(1.44)

Note(s): t statistics in parentheses, *p < 0.05, **p < 0.01, ***p < 0.001
Source(s): Own elaboration

Table 5.
System of equation
models for FDII, PED,
EGS and GVAC

In the first case, the causality relationship between FDI inflow and GVAC in all six models Austria, Germany, France, Belgium, the Netherlands and Switzerland are significant, and there is bidirectional causality between FDI and GVAC in Austria, Belgium and the Netherlands. Sayari *et al.* (2018) found a long-run negatively significant relationship between the value-added component and FDI in Western Europe. The negative impact of FDI in Western Europe is due to the changing trend in FDI inflow and its determinants due to global strategic and macroeconomic considerations. However, they also mention that the negative impact of FDI is exploratory for future research. Sjöholm (2016) finds a positive relationship between FDI and value addition. This positive relationship is due to structural changes in high-value-added activities in the economy over the last two decades. High value-added enhances investment and increases tax revenue.

In the second case, the causality relationship between FDI and PED in all models is significant and has bidirectional negative causality between PED and FDI in Austria, France, the Netherlands, Switzerland and Germany, and positive bidirectional causality in Belgium. The negative relationship between PED and FDI inflow means that an increase in FDI results in a decrease in environmental emissions, which is referred to as the pollution halo hypothesis. The positive and negative causality of FDI and PED in Western Europe can be understood through the contribution of production-based emissions. According to Liu and Fan (2017) trade emissions to gross production-based emissions in Western Europe account for more than 20% of direct fossil fuel emissions, while small countries such as Switzerland, Belgium and Sweden account for more than 50%. Demena and Afesorgbor (2020) find that FDI on environmental emissions in 65 primary studies is close to zero. However, if we consider heterogeneity, FDI significantly reduces environmental emissions.

In the third case, the causality relationship between FDI and EGS inflow shows bidirectional negative causality between FDI and EGS in Austria, Switzerland and the Netherlands, while for Belgium, France and Germany, it is insignificant. Conconi et al. (2016) found Western European countries, such as Belgium. Initially, firms may serve the foreign market by exporting because they are uncertain about their ability to earn profits in the host market. Thus, FDI is always preceded by exports, and around 90% of companies serve a foreign market through exports before they start investing in the host country. Finally, the causality results among FDI, PED, EGC and GVAC are similar to previous studies (Conconi et al., 2016; Sjöholm, 2016; Cole et al., 2017; Liu and Fan, 2017; Sayari et al., 2018).

5.1 Theoretical implications
Despite the policy implications for FDI inflows, drafting policy should focus on a rationally based policy instead of a reason-based policy. A policy based on the traditional statistical method is limited by the preoccupied assumption and preconceived opinion, which often bias the investment decision and diverge the FDI allocation. Further, in the advancement of ML, trusting the model and prediction are two different aspects to understand FDI investment decisions. A high-performance model does not guarantee that the created model is trustworthy for the practical world. Therefore, this creates a gap in predicting trustworthy and actual influencer variables of FDI investment. This can lead to policy failure. Further the policymaker should have to trust on a true framework that has interpretability, causation and effectiveness to the real world. This study suggested that the use of rigorous science can bring the rationality and overcome the biasness in policy making occurred by preoccupied mind.

5.2 Policy implication
In policymaking, the national government can understand through this framework how investors make capital allocation decisions in their country. The results of this study should not be used for naïve public policymaking. It considers that by focusing only on GVAC, PED and EGS can win the race of FDI inflow because investment attractiveness is a system that can also be affected by the other variables. The framework developed in this study can help policymakers better understand the rationality of FDI inflows.

5.3 Future research agenda and limitation
This study has several limitations. Ideally, the classification accuracy should be higher. The current scope is limited to examining the performance of FDI determinants within Western Europe. Moreover, the framework created in this study may be applied in another regions to test the FDI influencing factors. Since the FDI depends on the overall collective condition of a friendly business environment. Therefore, the future research may use this study framework to test the large and another set of variables.

6. Conclusions

This research achieved the following major objectives to determine the FDI determinants and present their global interpretation to understand their relationship with the prediction target. The author implemented an ML-based prediction system, which can play an important role in investment decisions. Further, the author presented a model-agnostic approach that can increase the trust level of foreign investors by creating IML reports. Emphasized along with high-accuracy models, a true framework should have interpretability, causation and effectiveness in the real world. Therefore, the most influential and important variable of FDI inflow and the causality among the FDII, GVAC, PED and EGS variables are presented. This study also discusses an extensive literature review of IML in the field of foreign investment.

The findings of this study show that ML models perform better than conventional linear regression models. Additionally, research shows that there is a difference between the most important factors (tax, GCF and PED) and the most trusted factors (PED, EGS and GVAC) for FDI inflow in Western Europe. Further, from the decision tree, the author visualizes the decision-making progress of FDI inflow in Western Europe. Furthermore, from the simultaneous equation, we find bidirectional causality between FDI and GVAC in Austria, Belgium and the Netherlands; bidirectional negative causality between PED and FDI in Austria, France, the Netherlands, Switzerland and Germany; positive bidirectional causality for Belgium; and bidirectional negative causality between FDI and EGS in Austria, Switzerland and the Netherlands.

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Appendix
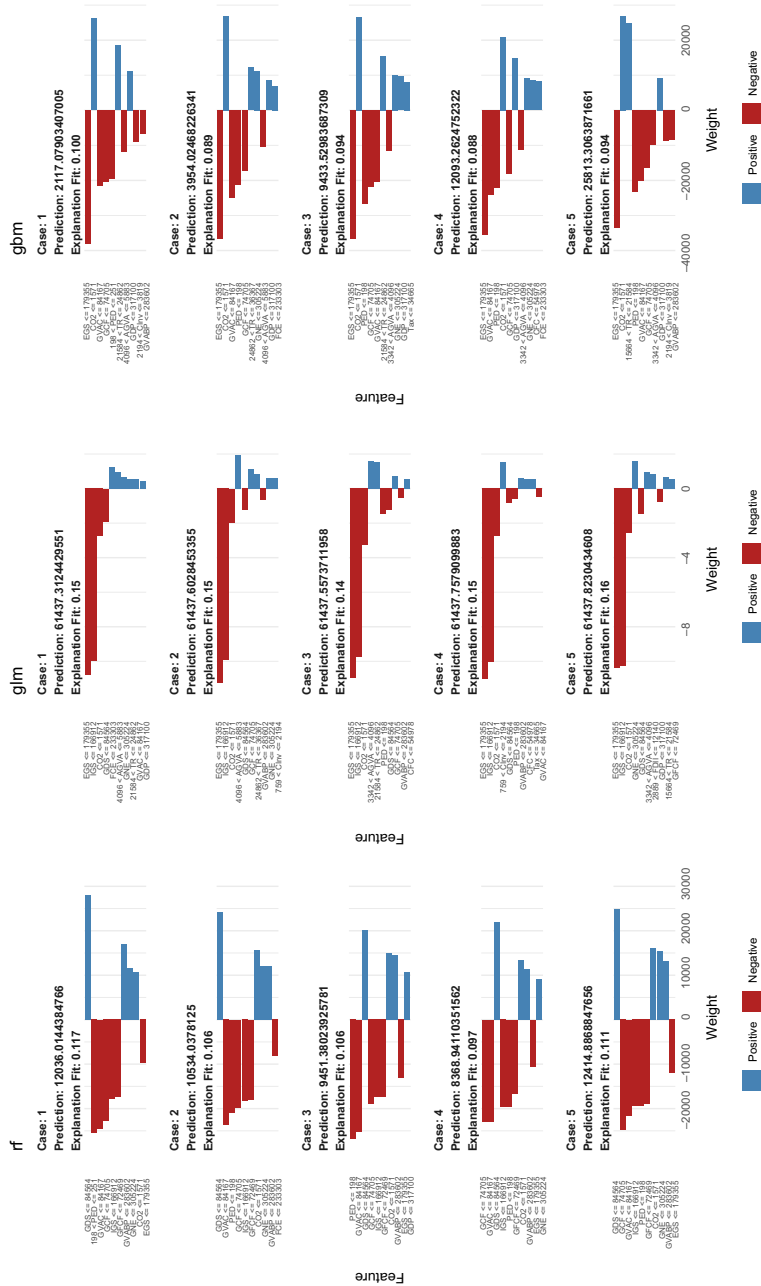
Source(s): Own elaboration

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