The impact of CSR performance on Efficiency of Investments using Machine Learning

Nadia Lakhal, Asma Guizani, Asma Sghaier, Mohammed El amine Abdelli, Imen Ben Slimene

UEH University of Economics Ho Chi Minh City

VIỆN NGHIÊN CỨU KINH DOANH
INSTITUTE OF BUSINESS RESEARCH

CFVG European Excellence in Management Education

ISB International School of Business

University of Leicester

CAU 중앙대학교 CHUNG-ANG UNIVERSITY

BINH DUONG UNIVERSITY

ĐẠI HỌC THỦ DẦU MỘT

CONFERENCE PROCEEDINGS

International Conference on Business and Finance 2021

Volume 2

NHÀ XUẤT BẢN LAO ĐỘNG

The Impact Of CSR Performance On Efficiency Of Investments Using Machine Learning

Nadia Lakhal[1], Asma Guizani[2], Asma Sghaier[3*], Mohammed El Amine Abdelli[4], Imen Ben Slimene[5]
[1] Department of Finance LaMIDED, University Of Sousse, Sousse, Tunisia.
[2] Department of MQ, CNAM de Paris , Musée des arts et métiers, Paris, France.
[3] Department of Finance, University Of Sousse, Sousse, Tunisia.
[4] IAE of Bretagne Occidentale, LEGO-University of Western Brittany-UBO, Brest, France.
[5]Department of Management, CREGO-University of Upper Alsace, Colmar, France.
*Corresponding Author: (Phone: +216 98459394; Email: asma.sghaier@ihecso.u-sousse.tn)

Abstract

This paper examines the relationship between investment decisions and a firm's engagement in corporate social responsibility (CSR) activities in a European context. More precisely, we seek to determine the impact of CSR performance on investment effectiveness by using machine learning to classify two basic models. We found that Richardson's method gives better results, therefore, increases the efficiency of investments. This result is in line with our expectations that companies with strong CSR have low information asymmetry and strong stakeholder solidarity regarding stakeholder theory.

Keywords: *CSR, Investment Efficiency, Machine learning, Stakeholder Theory*.

1. INTRODUCTION

In a world where capital markets are perfect, information is available, and debt financing is risk-free. Modigliani and Miller (1958)established that a company's investment decisions are separate from its finance decisions. The future cost of profitability and capital of a company's investment programs will determine its market value. The value of the company is associated in this respect with the optimal level of investment. However, the capital markets are not without flaws. Indeed, in the capital markets, information asymmetry and transaction costs can lead to agency issues, resulting in conflicts of interest between shareholders and managers (Jensen & Meckling, 1976). This interest divergence makes the possibility of deviation in the optimal level of investment very high, and companies will also face ineffective investment situations. Biddle, Hilary, and Verdi (2009)identified two types of inadequate investments: underinvestment, generally due to insufficient funding for positive net present value investments. The second is an excessive investment, described as investments in projects with a negative net worth.The investment decision is one of the main pillars of corporate finance. It is a kind of bet on the future, and the possibility of failure and making inadequate investments is very likely. At the macroeconomic level and when investors bet simultaneously on non-optimal investments, the possibility of moving from a simple recession to an economic crisis is very significant. Inadequate investment, also known as a lousy investment, can be an overinvestment of underinvestment. Underinvestment is a situation where companies have little cash and a high level of growth opportunities. At the same time, overinvestment is when companies have excess cash flow and low growth opportunities. Overly optimistic economic agents tend to over-invest and create excess production capacity concerning the actual market demand. The interest rate is the critical investment variable. When the interest rate is too high, the investment in the market will be reduced, even for profitable projects.It favors investment even in projects with meager profitability or negative net present value if it is too low. Managers' decisions about investing in suboptimal projects can only be rational when a conflict of interest exists between managers and shareholders. To increase the firm beyond its optimal size, managers undertake negative net present value investments. This phenomenon, which is due to the opportunistic behavior of the managers, is called a phenomenon of overinvestment. Two reasons motivate the managers to do this: the first mentioned by (Mueller, 1969), who believed that the manager tries to increase the resources under his control to increase his power. The second reason emerges from the works of (R. A. Lambert, Larcker, & Verrecchia, 1991; Murphy, 1985; Schmidt & Fowler, 1990), who highlighted the high dependence of compensation and the leader's reputation on the company's size. Jensen (1986) defined overinvestment as a magnitude that can only be observed at the end of the project's economic lifespan. Shareholders, also wishing to maximize their future wealth, must ensure an ex-ante assessment of the risk of over-investment.Two determinants of a company’s overinvestment risk were mentioned by (Jensen, 1986): the company's cash flows and the level of its growth opportunities. Indeed, companies with significant available funds and low growth opportunities may waste their funds in harmful net present value projects. Companies with limited funds but considerable growth opportunities will have to find the means to finance their profitable investments. Here, the risk of investing in unprofitable projects is lower. According to previous research, there are two key reasons firms stray from their expected investment levels: Conflicts between free cash flow agencies (Guariglia & Yang, 2016; Jensen, 1986) and information asymmetry (Biddle et al., 2009; Cutillas Gomariz & Sánchez Ballesta, 2014; Myers & Majluf, 1984). Each of these explanations causes distinct types of errors in the investment decision process. While free cash flow challenges can lead to overinvestment issues, asymmetric information amongst other stakeholders is frequently associated with underinvestment issues. According to the agency's theory activities, various control methods, including CSR initiatives, are said to assist decrease managerial opportunism and reduce asymmetric information(Lopatta, Buchholz, & Kaspereit, 2016; Waddock, 1996). As a result, CSR strategies could be used to monitor concerns like underinvestment and overinvestment. Several lines of research have investigated the attractive characteristics of CSR and found that it is related to better firm value (Lin, Ma, & Su, 2009), lower financial constraints (Cheng, Ioannou, & Serafeim, 2014), higher information quality (Cho, Lee, & Pfeiffer, 2013; Cui, Jo, & Na, 2018; Lopatta et al., 2016), and fewer agency conflicts (Waddock, 1996). Based on this stream of research, we examined whether and how CSR participation affects investment decisions. The main objective of this study is to explore the relationship between firms' investment decisions and a firm's engagement in CSR activities in a European context using Machine Learning.

2. LITERATURE REVIEW

In a world without friction, financial theory predicts that firms can achieve optimal levels of investment (Modigliani & Miller, 1958). However, inevitable disagreements contribute to inefficient investment, according to both theoretical and empirical literature. Moral hazard and adverse selection are two of the most discussed conflicts due to information asymmetry between managers and external investors. These flaws can lead firms to under-invest (spend less than the optimal level)) or over-invest (support more than the optimal level). According to the concept of moral hazard, personal knowledge held by managers, a conflict of interest between management and shareholders, and a lack of managerial oversight can drive managers to maximize their well-being and invest more than is necessary. Managers are better known than external investors in the adverse selection model, and they reward capital when it is overvalued. Rational investors are likely to ration and increase the cost of capital in response to this tendency, resulting in financial limitations and underinvestment (Biddle et al., 2009; R. LAMBERT, LEUZ, & VERRECCHIA, 2007).

Any aspect that serves to reduce knowledge asymmetry also helps to increase investment efficiency. For example, control methods, such as the accuracy of financial reporting, could help to improve management oversight and reduce information asymmetries and risk (Healy & Palepu, 2001; HOPE & THOMAS, 2008). Moreover, several studies have found that enterprises with high-quality financial information have higher investment efficiency, thus reducing the information asymmetry of the market(Biddle et al., 2009; Cheng et al., 2014; Cutillas Gomariz & Sánchez Ballesta, 2014). For a long time, corporate social responsibility has been debated for implementation. However, some researchers believe that CSR is linked to performance and high corporate value, low financial risk, reduced information asymmetry, easy access to financing, and the low cost of capital (El Ghoul, Guedhami, Kwok, & Mishra, 2011). On the other hand, other researchers believed that CSR activities are a source of conflict between shareholders and unnecessary costs that reduce resources and create competitive disadvantages compared to companies that do not pay social responsibility.

On the one hand, according to Benlemlih and Bitar (2018) findings, corporate social responsibility reduced the inefficiency of investments and thus increased the efficiency of investments. On the other hand, since financially constrained firms are more likely to experience underinvestment issues (Campello, Graham, & Harvey, 2010; Hubbard, 1998), CSR performance can be critical in strategic investment decisions. Furthermore, implementing CSR activities leads to improved CSR performance, which helps organizations access external funding (Cheng et al., 2014) and make all the desired investments (Stein, 2003). In line with this context, (Attig, Cleary, El Ghoul, & Guedhami, 2014); El Ghoul et al. (2011)found that firms with superior CSR performance have lower equity financing costs. This is true for firms that seek to improve their working relationships, environmental regulations, and product plans. (Dhaliwal, Li, Tsang, & Yang, 2011) also studied the advantages of the voluntary disclosure of CSR activities; the researchers clarified that companies that perform well on social responsibility had lower equity costs to attract specialized institutional investors and analyst coverage. According to (Sharfman & Fernando, 2008), firms that establish a strategy that improves their environmental risk management are rewarded by capital markets. The latter are willing to accept reduced risk premiums on equity, potentially lowering capital costs. Therefore, the cost of bank debt can be determined by CSR. Recently, in nations with weaker market institutions, (El Ghoul, Guedhami, Kim, & Park, 2018)found that CSR performance is related to better access to finance, higher investment, lower default risk, and longer commercial credit tenure.

Furthermore, according to Attig et al. (2014), CSR performance lowered the vulnerability of cash flows associated with investments. Moreover, Benlemlih and Bitar (2018) noted that performing CSR activities aids in the reduction of investment inefficiencies. Specifically, Employee interactions, diversity, the environment, and product features are essential factors to consider when improving investment efficiency. Generally, the following discussion explores that CSR performance is critical in strategic investment decisions and the Companies that invest more efficiently have a more excellent CSR performance.

3. METHODOLOGY

As a measure of overinvestment, Richardson (2006) breaks down the investment into two components: (1) necessary expenditures to maintain assets in place and (2) new investment expenditures. He then decomposed the new investment expenditure into overinvestment expenditure in harmful Net Present Value NPV projects and investment expenditures in expected projects, which vary according to firms' growth opportunities, financing constraints, industry affiliation...etc. According to Richardson (2006) , the total investment is the sum of all capital expenditures, acquisitions, and research and development minus revenues from the sale of goods, facilities, and equipment.

$I = CE + ACQ + RD - R_{SGIE}$

With:

I: total investment;

CE: capital expenditure;

ACQ: acquisition expenses;

RD: expenditure on research and development;

R_{SGIE}: revenue from the sale of goods, installation, and equipment.

Total investment expenditure can be divided into two main components: The first is the necessary capital investment to keep the assets in place, $I_{MAINTENANCE}$. It corresponds to expenses related to the amortization and depreciation of existing assets. The value of amortization and depreciation estimates the portion of the total investment expenditure required to maintain facilities, equipment, and other assets. The second component refers to investment expenditures on new projects, I_{New}. Subsequently, Richardson decomposed I_{New} into planned or expected capital expenditures in new projects with positive Net present values NPVs, $I_{New\,*}$, and into abnormal or unexpected investment expenditures, $I_{New}{}^{a}$. This distribution is illustrated as follows:

$$I = I_{\text{Maintenance}+}\, I_{New=}\, I_{\text{Maintenance}+}\, I_{New^{*}+}\, I_{New^{a}}$$

With:

$I_{Maintenance}$: expenses related to amortization and depreciation of existing assets;

I_{New}: investment expenditure in new projects;

I_{New} *: Planned or expected investment expenditure in new positive NPV projects;

$I_{New}{}^{a}$: abnormal or unexpected investment.

The abnormal component of the investment may be harmful or positive. Therefore, negative (positive) values are under (over) investment.

A vast literature on economics and finance has examined investment decisions at the firm's level (Hubbard, 1998). Richardson used this literature to estimate the expected investment according to the specification of this model:

$I_{New\ t} = \alpha + \beta_1 V/P_{t-1} + \beta_2\, Leverage_{t-1} + \beta_3\, Cash_{t-1} + \beta_4\, Age_{t-1} + \beta_5\, Size_{t-1} + \beta_6\, ROA_{t-1} + \beta_7\, I_{New\ t-1} + \sum$ Year Indicator + $\sum$ Industry Indicator

With:

$I_{New\ t}$: expenditure used to gain new investments in year t;

V/P_{t-1}: the value of Assets in place divided by the market value of the firm. This relationship measures growth opportunities.

$Leverage_{t-1}$: debt measured by the ratio of total debt to total assets;

Cash $_{t-1}$: cash and cash equivalents divided by the total assets at the beginning of the period;

Age $_{t-1}$: Neperian log of the number of years spent by the firm in the stock market;

Size $_{t-1}$: Neperian log of total assets at t-1. This variable is used to control the effect of the firm size on investment;

ROA $_{t-1}$: the profitability of the assets of the year t-1. It is calculated by the ratio between the net result and the total assets. The calculated value of the above regression is the estimate of the expected level of new investment, I_{New*}. The unexplained or residual part is the estimate of overinvestment, $I_{New}{}^{a}$. According to Biddle et al. (2009), the deviation from the expected investment using the investment forecasting model based on income growth is used to measure the efficiency of investments. Therefore, an investment deficit (negative gap concerning the expected investment) is ineffective (McNichols & Stubben, 2008). Biddle et al. (2009) examined whether a better quality financial reporting improves the efficiency of investments by reducing overinvestment or underinvestment. Biddle et al. (2009)used the following model to explain investment at the firm level to identify overinvestment and underinvestment.

$I_{t+1} = \beta_0 + \beta_1 SG_t + \varepsilon_t$

Biddle et al. (2009) sorted the observations in each year according to the model residuals to determine investment efficiency and classified observations in the bottom quartile as (underinvestment), while observations in the top quartile are classified as (overinvestment). Machine learning can be used to solve a variety of issues, including classification and regression analysis. Classification algorithms group observations into a finite number of categories. These Classification algorithms are far more commonly used in practice. They are based on probability, so the type with the highest probability of belonging determines the outcome.

Logistic regression

Logistic regression (Tenenhaus et al., 2007) is a multivariate model that explains, in probability form, the relationship between a dependent qualitative variable Y, often binary, $Y \in \{0, 1\}$, and one or more independent variables X that can be qualitative or quantitative.

The model provides the probability that an event will occur or not (in our case, default or non-default). The independent variables X are those likely to influence whether the event occurs. The logistic function is the following:

$$Y = P(Y = 1) = \beta_0 + \beta_1 . x_1 + \beta_2 . x_2 + \cdots + \beta_n . x_n + \cdots + \beta_k . x_k$$

With:

$$Y = \mathrm{Log}\left[\frac{p}{1 - p}\right]$$

And

$$p = \frac{e^{\beta_0 + \sum_{i=1}^{k} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{k} \beta_i x_i}}$$

It is enough to adjust this logistic regression model to determine the coefficients βof the equation (1.5) function, with k as the number of exogenous variables. It is enough to use the maximum likelihood method to estimate parameters that maximize the probability of obtaining the values observed on the sample.

Discriminative analysis

On a population of n individuals, we observe a qualitative variable Y to k modalities and p quantitative variablesX_i, $i = 1, \ldots, p$. The variable Y allows splitting the population into k disjoint groups.

With two groups ("E" for efficient firms and "I" for inefficient firms), the discriminative function is as follows:

$$f(X_i) = (m_E - m_I)W^{-1}(X_i - \frac{m_I + m_E}{2})$$

Where m_I is the average point of the group of inefficient firms, m_E is the average point of the group of efficient firms, and W is the intra-class variance-covariance matrix.

The assignment decision rule is as follows: if the discriminative function is more significant than a threshold "s," then the company is considered an efficient company; otherwise, it is assigned to the group of ineffective firms. The discriminative analysis then makes it possible to highlight the difference between classes and to find a decision rule based on the knowledge of Y and of X_i, allowing the assignment of a new individual (for which Y is unknown) to the closest group.

Neural networks

These are the works of McCulloch and Pitts (1943), who showed, for the first time, that neural networks could be applied in solving complex logical, arithmetic, and symbolic functions. The neural networks comprise an input layer (input variables), an output layer (output variables), and one or more hidden layers of processes that form the set of hidden nodes connected. Each layer takes its inputs on the outputs of the previous one. For this reason, if layer (i) is composed of N (i) neurons, they take their inputs on the neurons of the previous layer of the rank (i-1). Each neuron (or elementary process) receives a variable input number X_i from the upstream neurons.

A neural network can be schematized as follows:

Threshold b

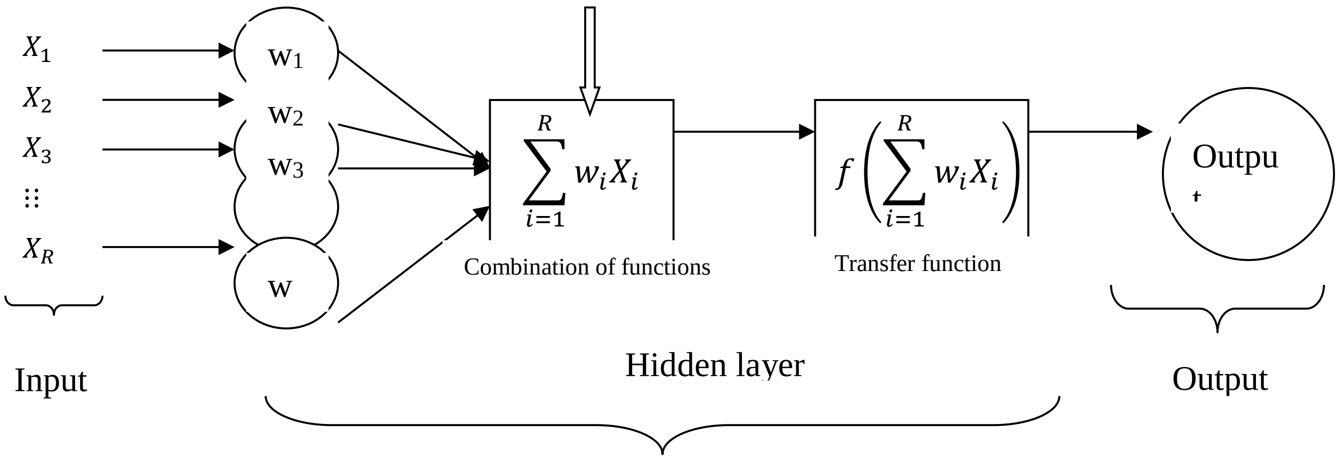

Fig.1: Design of a neural network, Source: Adapted from (Tufféry, 2011).

b: The neuron's bias or activation threshold.
X_i: Information that reaches the rank i neurons in the input layer
R: the number of information
w_iThe weighting of the signal emitted by the neuron from the input layer to the hidden layer neuron.

Boosting

The boosting introduced by Freund, Schapire, and Abe (1999) is a family of automatic learning algorithms whose purpose is to combine a set of so-called "weak" classifiers to arrive at a single "strong" classifier, hence the improvement of the classification's performance. The AdaBoost algorithm, used in our case, consists in assigning a weight to each observation of the learning sample; this weight corresponds to the level of difficulty encountered to predict the class of this individual. Thus, the algorithm begins by constructing the first classifier on all the learning data. Initially, all the weights are identical and used to build the first classifier, but during iterations, the data in a class that does not match them will have increasing weight, and those that are well placed in their classes will have decreasing weights.

Algorithm: AdaBoost (Friedman, Hastie, & Tibshirani, 2000):

Initialization: The set of learning data

$$S = \{(x_1, y_1), \cdots, (x_N, y_N)\}$$

with $x_i \in$ X described by p explanatory variables and $y_i \in$ Y={-1,1}.

Initial weights $w_0(i) = \frac{1}{N}$ with $i = 1, \dots, N$ .Do for t = 1, 2, ..., T:

- Build a classifier $f_t(x_i) \in \{-1, 1\}$ using weights and learning data.
- Calculate the weighted empirical risk:

  $\varepsilon_t(i) = \sum_i w_t(i) \mathbb{1}_{[y_i \neq f_t(x_i)]}, i = 1, \dots, N$

  If$\varepsilon_t > 0{,}5$**or if** all the observations are well classified, **then** we stop the process

  If not:

  i. Calculate $\alpha_t = \frac{1}{2} \log\left(\frac{(1-\varepsilon_t(i))}{\varepsilon_t(i)}\right)$

  ii. Update weights

$$w_{t+1}(i) = \frac{w_t(i)}{z_t} \times \begin{cases} e^{-\alpha_t} \text{si} f_t(x_i) = y & \text{- well classified} \\ e^{\alpha_t} \text{si} f_t(x_i) \neq y & \text{-misclassified} \end{cases} \quad i = 1, \dots, N$$

$$w_{t+1}(i) = \frac{w_t(i)\exp(-\alpha_t y_i f_t(x_i))}{z_t}$$

With z_t is a normalization factor

End:

The final classifier assigns a new observation to one class according to the sign of the classifier

$$\text{sign}[F(x)] = \text{sign}\left(\sum_{t=1}^{T} \alpha_t f_t(x_i)\right)\begin{cases} \text{si} F(x) > 0 \text{ alors} y = 1 \\ \text{si} F(x) < 0 \text{ alors} y = -1 \end{cases}$$

Random Forest

RF is a supervised learning algorithm introduced by (Breiman, 2001); it is considered a suitable method for classification problems. It brings together methods of aggregation, bagging, and decision trees. According to Breiman (1996), The principle of bagging is to build decision trees from different bootstrap samples. Then the idea is to modify the predictions to create a varied collection of predictors. The aggregation step then makes it possible to obtain a robust and more efficient predictor.

With the random forest method, which is an essential modification of the bagging, the objective is to build more independent trees to obtain a more efficient final model.

The algorithm is as follows:

Initialization: The set of learning data $S = \{(x_1, y_1), \cdots, (x_N, y_N)\}$with

$x_i \in X$ described by p explanatory variables and $y_i \in Y = \{-1, 1\}$

Do for t = 1, 2, ..., T: (T represents the number of trees formed in the forest)

- Draw a random sample S_t with discount among S
- Estimate a tree $S_t$with randomization of variables: For the construction of each tree node, one pulls uniformly q (to optimize the choice of q$\simeq \sqrt{p}$) variables among p to form the decision associated with the node.

At the end of the algorithm, we have T trees that we average or that we make vote for regression or classification.

4. RESULTS AND DISCUSSION

To predict the label of a new business, most business votes are used with classification or the average of the predictions of all decision trees with regression.

To compare the predicted and actual predictor variables (efficient and inefficient firms), we shared our initial sample in 70% of the learning sample to build our classification models for the different methods and 30% of the sample test used to compare these models obtained by estimating the forecast error from the confusion matrix or by calculating the air under the ROC curve.

4.1. The confusion matrix

The evaluation of the decision rule for this method is often based on estimating the error rate. The following table, named assignment table or confusion matrix, presents the different possibilities of assigning an observation to a class by a model, making it possible to estimate the rate of reasonable classifications and the error rate.

TABLE1. : Confusion Matrix

Table 18. Confusion Matrix

	Assignments	
Actual situation	Bad payer	Good payer
Bad payer	RTN	RFP
Good payer	RFN	RTP

With:

- RTP: Rate of true positives (efficient enterprises classified as such).

- RFP: Rate of false positives (inefficient firms classified as effective).

- RTN: Rate of true negatives (inefficient firms classified as such).

- RFN: Rate of False negatives (efficient enterprises classified as ineffective).

It is noted that:

• **Type 1 error**: represents the inefficient firms declared by the model as effective.

• **Type 2 error**: represents efficient firms, qualified by the model as inefficient firms. Each misclassification generates an additional cost related to the wrong decision one would have made. It is then minimizing this cost caused by the incorrect classification of the elements.

4.2. The Receiver Operating Characteristic Curve (ROC)

The ROC curve is a graphical representation of the performance of two-class classifiers; it relates the proportion of true positives (efficient firms classified as such) to the ratio of false negatives (inefficient firms classified as efficient) when we vary the assignment threshold.

The study of the models' performance is done by comparing their AUC (Area Under the Curve) indices, the areas under their ROC curves. A model is even more powerful when its AUC is closer to 1, and it is even less powerful when its AUC is close to zero. Where the AUC is equal to 0.5, the model is uninteresting.

The following table gives the error rate results and the AUC value for each method for the test sample.

Table 19: Error Rate Findings and Results

	Biddle's Investment		**Richardson's Investment [1]**		**Richardson's Investment [2]**	
Methods	**ERROR RATE**	**AUC**	**ERROR RATE**	**AUC**	**ERROR RATE**	**AUC**
Logisticregression	25.75%	0.737	5.57%	0.906	17.90%	0.788
Linear discriminative analysis	25.21%	0.776	6.39%	0.905	18.08%	0.788
Neural networks	12,79%	0.848	4.29%	0.921	2.01%	0.985
Boosting	0%	0.980	0%	0.993	0%	0.986
Randomforest	0.09%	0.985	0%	0.991	0%	0.983

We can notice that all the methods predict well the effective business category. We also see that the two boosting and RF algorithms both have error rates of 0%; They affect the firms to their respective categories without error and have the highest AUCs (very close to 1). Therefore, they have perfect predictive power.

This is explained because their main objective is to train the initial classifier until the last iteration obtains an effective and efficient final classifier.

The neural networks also give perfect results (an error rate equal to 12.79% for the Biddle method, 4.29% for the first method of Richardson, and 2.01% for the last method) compared to conventional classification methods (logistic regression and discriminative analysis), which have the least effective results compared to others. We note that Richardson's approach gives better outcomes for all methods than those provided by the Biddle method. From the results found, we can conclude that implementing CSR activities help reduce the inefficiency of investments.

5. CONCLUSION

This study's main objective is to examine the relationship between corporate investment decisions and a firm's engagement in corporate social responsibility (CSR) activities in a European context. In addition, we aim to determine whether and in what way CSR performance influences investment effectiveness. For this study, we employed machine learning to classify two basic models of investment effectiveness measurement of (Biddle et al., 2009; Richardson, 2006). The main results of our study illustrate that Richardson's method gives better outcomes for all strategies than those provided by (Biddle et al., 2009) process. Moreover, we may conclude that strong CSR participation decreases investment inefficiency and, consequently, increases investment efficiency. This result aligns with our expectation that firms with strong CSR benefit from low information asymmetry and strong stakeholder solidarity (stakeholder theory). Finally, the implication of the Corporate Social Responsibility into a new governance model is to achieve a systematic, practical, coordinated, and efficient implementation of a sustainable approach and enhance the culture of ethics and the global responsibility at the board, organization, and company network level. In this context, National and international institutions, governments, investors, and communities play a critical role in urging firms to pay close attention to CSR and sustainability matters.

REFERENCES

Attig, N., Cleary, S. W., El Ghoul, S., & Guedhami, O. (2014). Corporate Legitimacy and Investment–Cash Flow Sensitivity. *Journal of Business Ethics*, *121*(2), 297-314. doi:10.1007/s10551-013-1693-3.

Benlemlih, M., & Bitar, M. (2018). Corporate Social Responsibility and Investment Efficiency. *Journal of Business Ethics*, *148*(3), 647-671. doi:10.1007/s10551-016-3020-2

Biddle, G. C., Hilary, G., & Verdi, R. S. (2009). How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics*, *48*(2), 112-131. doi:https://doi.org/10.1016/j.jacceco.2009.09.001

Breiman, L. (1996). Bagging predictors. *Machine Learning*, *24*(2), 123-140. doi:10.1007/BF00058655

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*(1), 5-32. doi:10.1023/A:1010933404324

Campello, M., Graham, J. R., & Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, *97*(3), 470-487. doi:https://doi.org/10.1016/j.jfineco.2010.02.009

Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic Management Journal*, *35*(1), 1-23. doi:https://doi.org/10.1002/smj.2131

Cho, S. Y., Lee, C., & Pfeiffer, R. J. (2013). Corporate social responsibility performance and information asymmetry. *Journal of Accounting and Public Policy*, *32*(1), 71-83. doi:https://doi.org/10.1016/j.jaccpubpol.2012.10.005

Cui, J., Jo, H., & Na, H. (2018). Does Corporate Social Responsibility Affect Information Asymmetry? *Journal of Business Ethics*, *148*(3), 549-572. doi:10.1007/s10551-015-3003-8

Cutillas Gomariz, M. F., & Sánchez Ballesta, J. P. (2014). Financial reporting quality, debt maturity and investment efficiency. *Journal of Banking & Finance*, *40*, 494-506. doi:https://doi.org/10.1016/j.jbankfin.2013.07.013

Dhaliwal, D. S., Li, O. Z., Tsang, A., & Yang, Y. G. (2011). Voluntary Nonfinancial Disclosure and the Cost of Equity Capital: The Initiation of Corporate Social Responsibility Reporting. *The Accounting Review*, *86*(1), 59-100. doi:10.2308/accr.00000005

El Ghoul, S., Guedhami, O., Kim, H., & Park, K. (2018). Corporate Environmental Responsibility and the Cost of Capital: International Evidence. *Journal of Business Ethics*, *149*(2), 335-361. doi:10.1007/s10551-015-3005-6

El Ghoul, S., Guedhami, O., Kwok, C. C. Y., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance*, *35*(9), 2388-2406. doi:https://doi.org/10.1016/j.jbankfin.2011.02.007

Freund, Y., Schapire, R., & Abe, N. (1999). A short introduction to boosting. *Journal-Japanese Society For Artificial Intelligence*, *14*(771-780), 1612.

Friedman, J., Hastie, T., & Tibshirani, R. (2000). Additive logistic regression: a statistical view of boosting (With discussion and a rejoinder by the authors). *The Annals of Statistics*, *28*(2), 337-407, 371. Retrieved from https://doi.org/10.1214/aos/1016218223

Guariglia, A., & Yang, J. (2016). A balancing act: Managing financial constraints and agency costs to minimize investment inefficiency in the Chinese market. *Journal of Corporate Finance*, *36*, 111-130. doi:https://doi.org/10.1016/j.jcorpfin.2015.10.006

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics, 31*(1), 405-440. doi:https://doi.org/10.1016/S0165-4101(01)00018-0

HOPE, O.-K., & THOMAS, W. B. (2008). Managerial Empire Building and Firm Disclosure. *Journal of Accounting Research, 46*(3), 591-626. doi:https://doi.org/10.1111/j.1475-679X.2008.00289.x

Hubbard, R. (1998). Capital-Market Imperfections and Investment. *Journal of Economic Literature, 36*(1), 193-225. Retrieved from https://EconPapers.repec.org/RePEc:aea:jeclit:v:36:y:1998:i:1:p:193-225

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review, 76*(2), 323-329. Retrieved from http://www.jstor.org/stable/1818789

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305-360. doi:https://doi.org/10.1016/0304-405X(76)90026-X

LAMBERT, R., LEUZ, C., & VERRECCHIA, R. E. (2007). Accounting Information, Disclosure, and the Cost of Capital. *Journal of Accounting Research, 45*(2), 385-420. doi:https://doi.org/10.1111/j.1475-679X.2007.00238.x

Lambert, R. A., Larcker, D. F., & Verrecchia, R. E. (1991). Portfolio Considerations in Valuing Executive Compensation. *Journal of Accounting Research, 29*(1), 129-149. doi:10.2307/2491032

Lin, C., Ma, Y., & Su, D. (2009). Corporate governance and firm efficiency: evidence from China's publicly listed firms. *Managerial and Decision Economics, 30*(3), 193-209. doi:https://doi.org/10.1002/mde.1447

Lopatta, K., Buchholz, F., & Kaspereit, T. (2016). Asymmetric Information and Corporate Social Responsibility. *Business & Society, 55*(3), 458-488. doi:10.1177/0007650315575488

McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics, 5*(4), 115-133. doi:10.1007/BF02478259

McNichols, M. F., & Stubben, S. R. (2008). Does Earnings Management Affect Firms' Investment Decisions? *The Accounting Review, 83*(6), 1571-1603. doi:10.2308/accr.2008.83.6.1571

Modigliani, F., & Miller, M. H. (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review, 48*(3), 261-297. Retrieved from http://www.jstor.org/stable/1809766

Mueller, D. C. (1969). A Theory of Conglomerate Mergers*. *The Quarterly Journal of Economics, 83*(4), 643-659. doi:10.2307/1885454

Murphy, K. J. (1985). Corporate performance and managerial remuneration: An empirical analysis. *Journal of Accounting and Economics, 7*(1), 11-42. doi:https://doi.org/10.1016/0165-4101(85)90026-6

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics, 13*(2), 187-221. doi:https://doi.org/10.1016/0304-405X(84)90023-0.

Richardson, S. (2006). Over-investment of free cash flow. *Review of Accounting Studies, 11*(2), 159-189. doi:10.1007/s11142-006-9012-1.

Schmidt, D. R., & Fowler, K. L. (1990). Post-acquisition financial performance and executive compensation. *Strategic Management Journal, 11*(7), 559-569. doi:https://doi.org/10.1002/smj.4250110706

Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic Management Journal, 29*(6), 569-592. doi:https://doi.org/10.1002/smj.678.

Stein, J. C. (2003). Chapter 2 - Agency, Information and Corporate Investment. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of the Economics of Finance* (Vol. 1, pp. 111-165): Elsevier.

Tenenhaus, A., Giron, A., Viennet, E., Béra, M., Saporta, G., & Fertil, B. (2007). Kernel logistic PLS: A tool for supervised nonlinear dimensionality reduction and binary classification. *Computational Statistics & Data Analysis, 51*(9), 4083-4100. doi:https://doi.org/10.1016/j.csda.2007.01.004

Tufféry, S. (2011). *Data mining and statistics for decision making*: John Wiley & Sons.

Waddock, S. A. (1996). Strategy, structure, and social performance: Implications of the W-form enterprise. *Business and the Contemporary World, 8*, 43-51.

CONFERENCE PROCEEDINGS
INTERNATIONAL CONFERENCE ON
BUSINESS AND FINANCE 2021

NHIỀU TÁC GIẢ

----------------*----------------

NHÀ XUẤT BẢN LAO ĐỘNG
175 Giảng Võ, Hà Nội
ĐT: 024.38515380 - Fax: 024.38515381
Email: info@nxblaodong.com.vn
Website: www.nxblaodong.com.vn

CHI NHÁNH PHÍA NAM
85 Cách Mạng Tháng Tám, Q.1, TP. HCM
ĐT: 028.38390970 - Fax: 028.39257205
Email: cn-nxbld@vnn.vn

Chịu trách nhiệm xuất bản:
Giám đốc, Tổng biên tập
Mai Thị Thanh Hằng

Biên tập: **Hồ Thị Phương Lan**
Sửa bản in: Trần Thị Hồng Hậu
Trình bày: Nguyễn Thị Ngân
Bìa: Nguyễn Phan Trúc Phương

Mã số ISBN
978 – 604 – 325 – 669 - 7

LIÊN KẾT XUẤT BẢN
Viện Nghiên cứu kinh doanh - Trường Đại học Kinh tế TP.HCM
59C Nguyễn Đình Chiểu, Phường 6, Quận 3, TP.HCM

In 200 cuốn, khổ 19.5 x 27 cm tại Công ty TNHH Thiết kế Quảng cáo Bao bì Anh Huy
Số xác nhận ĐKXB: 2014 – 2021/CXBIPH/02-111/LĐ
Quyết định xuất bản số: 53/QĐ-NXBLĐ cấp ngày 07/09/2021
In xong và nộp lưu chiểu năm 2021

ISBN 978-604-325-669-7

9 786043 256697

Sách không bán

ICBF 2021

icbf2021.sciencesconf.org