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ESG Performance and Portfolio Selection: The Case of the French Market

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Abstract

This article analyzes the effect of environmental, social, and governance (ESG) criteria on the choice and performance of financial portfolios. The study focuses on a sample of nine French industrial companies from the CAC 40, over the period from October 2016 to December 2022, divided into two sub-periods (before and during the crisis) using the k-means method. Three portfolios were constructed using genetic algorithms, according to the companies' ESG score level (high, medium, low), then compared using the stochastic dominance approach. The results show that before the crisis, portfolios with a high ESG score dominate others according to second- and third order. However, this dominance disappears during the crisis, highlighting the sensitivity of ESG performance to market conditions.

Keywords: *ESG Performance, Portfolio Selection, Stochastic Dominance, Genetic Algorithms, K-Means Clustering.*

Introduction

According to Friedman (1970), the primary purpose of business is to maximize profits for shareholders, the firm's only true responsibility according to this view. Thus, businesses do not have duties to society as a whole, but only to their shareholders. However, this traditional conception has been widely challenged in recent decades. With the rise of corporate social responsibility (CSR), societal expectations of businesses have evolved. The European Commission (2011) defines CSR as "a concept that designates the voluntary integration by companies of social and environmental concerns into their business activities and their relationships with their stakeholders." This approach broadens the corporate mission beyond purely financial objectives to include social, environmental, and ethical dimensions. This evolution does not only concern businesses themselves. Consumer behavior has also changed, with a growing desire to consume more responsibly, whether for environmental or social reasons. This underlying trend is also influencing investors, who are now directing their investment decisions toward companies that meet non-financial criteria. These criteria, grouped under the acronym ESG (environmental, social, and governance), have become key indicators for assessing a company's commitment to sustainable development. This development has sparked growing interest in academic research, particularly in exploring the link between ESG performance and the financial performance of companies, particularly that of their stock market shares. In this context, our study aims to analyze the impact of ESG criteria on the performance of financial portfolios and to assess their influence on portfolio selection decisions.

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Section 2 presents ESG criteria and Literature Review. Section 3 presents the database and the study period. Section 4 explains our methodology. Section 5 discusses our results. Section 6 concludes.

Literature Review

ESG analysis is based on three fundamental dimensions: Environmental, Social, and Governance, which constitute the pillars of the non-financial assessment of companies. These criteria allow us to understand a company's contribution to sustainable development, as well as its ethical behavior towards all its stakeholders. The environmental pillar refers to the impact of the company's activities on the natural ecosystem. It encompasses aspects such as greenhouse gas emissions management, energy consumption, use of natural resources, waste management, pollution (air, water, and soil), as well as adaptation and resilience to climate change. The social pillar concerns the company's relationships with its employees, customers, suppliers, and local communities. It includes criteria such as respect for human and labor rights, occupational health and safety, diversity and inclusion policies, employee training, as well as actions to promote social cohesion and reduce inequalities. The governance pillar focuses on the company's management, control, and transparency mechanisms. It examines, in particular, the composition and independence of the board of directors, executive compensation policies, the fight against corruption, the quality of financial reporting, and relations with shareholders and other stakeholders.

Thus, ESG criteria make it possible to assess the responsible behavior of companies with a view to long-term sustainability and are an increasingly used tool in asset allocation and portfolio management decisions. Early CSR-related research from stakeholder theory provides the basis for the ESG framework. Stakeholder theory suggests that its relationship with its stakeholder groups determines a firm's potential to create sustainable wealth (Garcia and al., 2017). Firms should therefore be transparent in disclosing corporate data, which reduces information asymmetry and leads to greater investor confidence. The study conducted by Friedeand al. (2015) indicates that financial markets have not shown any strong learning impact in the ESG-financial performance relationship so far, and primary studies since the 1990s have shown a trend of positive correlation. Indeed, many studies report a positive relationship between ESG performance and firm value or profitability. In this framework, Garcia and Orsato (2020) find a positive and statistically significant relationship between ESG performance and financial performance. Similarly, a study conducted in emerging markets in Latin America found that ESG scores are negatively associated with financial performance in Latin American multinational companies (Duque-Grisales and Aguilera-Caracuel, 2019). Similarly, Yoon and al., (2018) examine the case of 705 Korean companies for the period from 2010 to 2015, they find that these CSR practices have a positive and significant impact on the market value of the companies. The same finding was concluded by Zhou and al (2022), who conducted a study on Chinese listed companies. Other articles, however, suggest that ESG performance has a negative impact on the financial performance of the company. Jyoti and khanna (2021) and Rahi et al (2022) suggested that the relationship between ESG score and financial performance is statistically negative. Similarly, Demers et al. (2021) found that ESG performance did not contribute to US stock market returns during the 2020 crisis.

Data

Our database contains the monthly prices of French industrial companies in the CAC 40 index. The database used is composed of 9 CAC 40 companies with the period from October 2016 to

December 2022, generating a total of 74 monthly observations. Stock prices are transformed into returns by applying the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where:

• R_t: return at time t

• P_t = stock price at time t

• P_{t-1} = stock price at time t – 1.

To represent ESG in our analysis, we chose the overall ESG score, for each company, which represents all aspects of ethical and sustainable development criteria. The ESG score used varies between a value of 40.42 and 88.5.All these data were collected from the DataStream database.

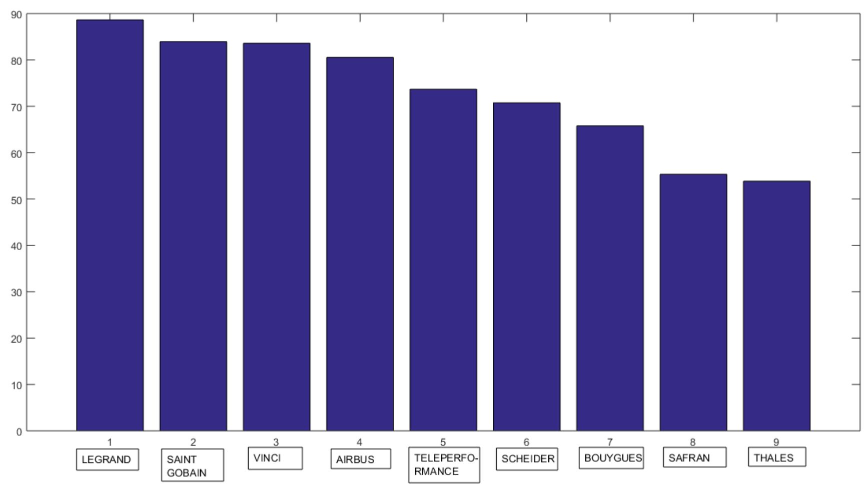

Figure 1: ESG Scores by Company

Our study period is divided into two sub-periods, before and during the Covid19 crisis, by applying the K-meansclustering method.

- **k-meansclustering method**

1) Objective: Minimize intra-cluster inertia

K-Means aims to partition a set of n points into k clusters $C_1, C_2, \dots, C_k$by minimizing the sum of the squared distances between each point and the center of its cluster.

Objective function:

$$\boldsymbol{argmin_{\mu_1 \mu_2 \dots \mu_k} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2} \quad \textbf{(1)}$$

μ_i : The center of the cluster C_i.

x : A data point.

$\|x-\mu_i\|^2$: The squared Euclidean distance between $x$and μ_i .

2) Computation Steps

a. Initialization

• Randomly choose

b. Assign points to clusters

Each point xx is assigned to the cluster with the closest centroid, minimizing the Euclidean distance:

$$C_i = \left\{ \boldsymbol{x} : \|\boldsymbol{x}-\boldsymbol{\mu}_i\|^2 \leq \left\|\boldsymbol{x}-\boldsymbol{\mu}_j\right\|^2, \forall_{j\neq i} \right\} \quad \textbf{(2)}$$

c. Updating Centroids

For each cluster C_i, recalculate the centroid as the average of the points assigned to that cluster:

$$\boldsymbol{\mu}_i = \frac{1}{|C_i|}\sum_{x\in C_i} \boldsymbol{x} \quad \textbf{(3)}$$

$|C_i|$: the number of points in the cluster C_i.

$\sum_{x\in C_i} x$: the sum of the points assigned to C_i.

d. Repetition

Repeat steps b and c until convergence is reached, that is:

• When the centroids no longer change significantly, or

• When the maximum number of iterations is reached.

According to this method, the pre-crisis period is between October 2016 to February 2020, and the crisis period is between March 2020 to December 2022 as shown in the figure below:

Figure 2: Evolution of Company Return

Methodology

In order to study the impact of ESG criteria on the performance of financial portfolios, we created three portfolios. The first portfolio contains French industrial companies with a high

ESG score, the second portfolio is composed of those with a medium ESG score and the third is composed of those with a low score, for two periods: before and during the crisis.

We will classify the companies in our sample according to the importance of the overall ESG score in 3 groups. Indeed, we calculated the average of the ESG score for each company for the two sub-periods. Then we ranked all the companies in ascending order for each period. Then we calculated the average of all ESG scores, i.e. 72.90 before the crisis and 76.97 during the crisis, and we chose all the companies that had a score ≥ 72.90 before the crisis and ≥ 76.97 during the crisis, and we formed the first group with a high ESG score. Secondly, we calculated the average for the rest of the companies, i.e. 61.43 before the crisis and 68.12 during the crisis, and similarly we selected the companies that had an ESG score ≥ 61.43 before the crisis and ≥ 68.12 during the crisis, and we formed the second group with a moderate ESG score. The remaining companies formed the third group with a low ESG score.Then, we will apply the genetic algorithm method, which aims to optimize the three portfolios during each period. And finally, we will use the stochastic dominance approach which allows us to compare two by two the performance of the portfolios for the two sub-periods.

Presentation of Genetic Algorithms and Their Applications in Finance

The Genetic algorithm is an exploration algorithm based on the mechanisms of natural selection and genetics proposed for the first time by John Holland 1975. They are based on the principles of survival of the most suitable structures. Each generation, a new set of artificial creatures (encoded as strings) is constructed from the best elements of the previous generation. Although relying heavily on chance (and therefore on a random number generator) these algorithms are not purely random.

In recent years, there has been a boom in the application of genetic algorithms to solve the problem of multi-objective optimization known as scalable multi-objective optimization or genetic multi-objective optimization. The fundamental characteristic of genetic algorithms is the multidirectional and global search, in which a population of potential solutions is maintained from generation to generation.

Numerous studies have shown that GA can efficiently find optimal solutions for many combinatorial optimization problems. Such as the study of Soleimani et al 2009 where he proposed GAs to address real markets with a large number of assets.

Pereira (2000) argues that genetic algorithms are a valid approach for many practical problems in finance that can be complex and therefore require the use of an efficient and robust optimization technique. Some applications of genetic algorithms to complex financial market problems include: yield forecasting, portfolio optimization, trading rule discovery, and optimization of trading rules. Rivera and al (2015) found that genetic algorithms are the most used approach for financial applications. In addition, Daiand al (2009) reported that GAs show promising results in financial applications and that GAs are also very effective for portfolio selection problem.

Optimization By Genetic Algorithm

A genetic algorithm is an iterative method of finding the optimal solution. It manipulates a population of constant size. This population consists of candidate points called chromosomes. This algorithm leads to a phenomenon of competition between chromosomes. Each chromosome is the encoding of a potential solution to the problem to be solved, it consists of a set of elements called genes, which can take several values. At each iteration (generation), a new population is created with the same size. This generation consists of the best "adapted" chromosomes to their environment. Gradually, the chromosomes tend towards the optimum of the fitness function. The convergence to a chromosome of high physical activity is done through genetic algorithm operators (selection, crossing and mutation).

The genetic algorithm randomly begins with a population generation 'k'. Three genetic operations (selection, crossing and mutation) are repeated for the elements of the population 'k' in order to move to a second generation 'k + 1'. Beginning with the first genetic operation, that is, the selection, which optimizes the objective function by selecting the relevant elements. The cross is the main genetic operator. It operates on two parents (chromosomes) at a time and generates two new chromosomes by combining the two characteristics of the "parent" chromosomes. In the case of weight selection problem, the crossing plays the role of exchanging weights of the securities that make up the portfolio. There are some forms of crossing: one point, two points, multipoint and uniform.

Finally, mutation is a background operator that produces spontaneous random changes in various chromosomes. The mutation is used to maintain the diversity of individuals in a population in order to prevent the premature convergence of solutions. A crossover operation creates new, remote individuals in the search space of their parent individuals. Therefore, the mutation operation can be considered as a small perturbation on the chromosomes of an individual that improves the exploration of the search space.

The Mathematical Formulation of the Objective Function in a GA Application

This sub section introduces the problem of Mult objective portfolio optimization and MOGA’s approach to solving this problem.

The evaluation is performed using the objective function which depends on the specific problem and the optimization objective of the genetic algorithm (Petridis *et al.*, 1998). The objective is to deter-mine the optimal proportions associated with each asset to maximize returns and minimize portfolio risk. The mathematical model, which is an expanded form of the Markowitz MV approach, is presented as follows:

$$Min\ \delta^2{}_p(w) = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} \quad (4)$$

$$Max r_p(w) = \sum_{i=1}^{n} \mu_i w_i \quad (5)$$

Under the contraints :$\sum_{i=1}^{n} w_i = 1$ et $w_i \geq 0, i = 1, \dots, n$ (6)

$\delta^2{}_p$: Portfolio variance;

r_p : the return of the portfolio;

σ_{ij} : the covariance between the returns of assets i and j;

w_i : the weight of each asset in the portfolio;

μ_i : the average yield of assets i.

In general, single objective optimization aims to find an optimal overall solution, however, multi-objective optimization aims to find a set of Pareto's optimal overall solutions. Since then, there are two conflicting objectives to optimize. In this study, the problem of optimizing multi-objective portfolios is replaced by as follows:

$MinH(w) = \delta^2{}_p(w) - r_p(w)$ (7)

Subject to :$\sum_{i=1}^{n} w_i = 1$ et $w_i \geq 0, i = 1, \dots, n$

Fitness Function

The fitness function is another important aspect of GA for solving optimization problems. In optimizing asset allocation, the fitness function must make a rational compromise between risk reduction and maximizing returns. Thus, it can be designed as follows:

$MinH(w) = \delta^2{}_p(w) - r_p(w)$ (8)

Such that: $\sum_{i=1}^{n} w_i = 1$ et$w_i \geq 0, i = 1, \dots, n$

The fitness function of each chromosome is the indicator that allows GA to make the selection.

Stochastic Dominance

According to Markowitz (1952), investors optimally estimate efficient portfolios by minimizing risk, as measured by standard deviation, for a desired level of return or maximizing returns for a given level of risk. Markowitz's (1952) mean-variance (MV) model is frequently used to control risk and assess portfolios. The main criticism of this model is that it assumes the normality of the distribution of returns, which is not always the case. For this purpose, if the distribution of returns is not normal, the results could be biased and misleading.

To overcome the limitations of the mean-variance (MV) approach, academics suggest adopting the rules of SD stochastic dominance, Developed by Hadar and Russell (1969), and others. The main advantage of using this approach is that it provides a very general framework for evaluating portfolio selection without the need for asset price benchmarks. In addition, it is based on less restrictive assumptions than the mean-variance method, satisfies the general utility function assumptions and takes into account all distribution. Whereas the MV approach takes into account only the first two moments. The DS approach has been considered one of the most useful tools for classifying investment perspectives (see, for example, Levy (1992). Several authors have applied stochastic dominance such as Abidand al. 2014) who used the stochastic dominance method to compare the performance of the two national and international portfolios Meyer, Li and Rose (2005) use DS criteria to examine whether the inclusion of foreign assets in a domestic portfolio generates diversification benefits Similarly, Lean and al. (2015) apply the stochastic dominance method to determine whether gold performs well for the diversification of French portfolios.

Let X and Y be two real random variables, with their cumulative distribution functions (CDFs)F_x and $F_y$and their probability density functions (PDFs)$f_x and f_y$ respectively, defined on the common support [n, m] with n <m. We define:

H0=h and $H_j(a) = \int_n^a H_{j-1}(t)dt$,(9)

For h = f_x ,f_y , H = F_x, F_y and j = 1,2,3.

The most widely used stochastic dominance (SD) rules are: first-order stochastic dominance 'FSD', second-order stochastic dominance 'SSD' and third-order stochastic dominance 'TSD '. Under FSD, all investors are non-satiated (that is, prefer higher return to less) under FSD, non-satiated and risk-averse under SSD, and non-satiated, risk-averse, and possessing decreasing absolute risk aversion (DARA) under TSD.

We define the fact that X is stochastically dominated by Y at order1 noted, $X \prec^{st1} Y$, as follows: $X \prec^{st1} Y \leftrightarrow F_{x1} \geq F_{y1} \leftrightarrow F_{x1}(a) \geq F_{y1}(a)$ for all possible returns a ϵ [n,m] with a strict inequality for some a. Stochastic dominance at order 1 will only be valid if the cumulative distribution functions of the alternatives do not intersect. We can say that if X is stochastically dominated by Y at order 1 if there is an arbitrage opportunity between X and Y so that investors will increase their expected wealth, as well as their expected utility, if their investments are spent from $X$to$Y$. On the other hand, if FSD does not exist between $X$and$Y$, we can conclude that the markets are efficient and investors are rational.

We define the fact that X is stochastically dominated by Y at order2 noted, $X \prec^{st2} Y$, as follows: $X \prec^{st2} Y \leftrightarrow F_{x2} \geq F_{y2} \leftrightarrow F_{x2}(a) \geq F_{y2}(a)$ for all possible returns a ϵ [n,m] with a strict inequality for some a. In this case, the two distribution functions of X and Y intersect. Indeed, for any possible value of a, the air under $F_{x2}$is larger than that underF_{y2}.

We define the fact that X is stochastically dominated by Y at order3 noted, $X \prec^{st3} Y$, as follows: $X \prec^{st3} Y \leftrightarrow F_{x3} \geq F_{y3} \leftrightarrow F_{x3}(a) \geq F_{y3}(a)$ for all possible returns a ϵ [n,m] with a strict inequality for some a.

We note that there is a hierarchical relationship in stochastic dominance. FSD implies SSD, which, in turn, implies TSD. However, the opposite is not true: the existence of SSD does not imply the existence of FSD. Likewise, the existence of TSD does not imply the existence of SSD or FSD.

There are two main classes of Stochastic Dominance tests: one is the minimum / maximum statistic (Barrett and Donald 2003, Linton (2005), and the other is based on distribution values calculated on a set of grid points (DD) Davidson, R .; Duclos, JY (2000). Since the DD testis one of the most powerful tests, we apply it in our analysis.

For two assets X et Y with their cumulative distribution functions $F_x$etF_y,respectively, and for a grid of pre-selected points $a_1, a_2, \ldots a_k$,, the order-j DD statistic, Tj (a) (j = 1, 2 et 3), is:

$$\hat{T}_j(a) = \frac{\hat{F}_{xj}(a) - \hat{F}_{yj}(a)}{\sqrt{\hat{V}_j(a)}} \quad , (10)$$

Where:

$$\hat{V}_j(a) = \hat{V}_x^j(a) + \hat{V}_y^j(a) - 2\hat{V}_{x,y}^j(a),$$

$$\hat{H}_j(a) = \frac{1}{N(j-1)!} \sum_{i=1}^{N} (a - h_i)_+^{j-1},$$

$$\hat{V}_H^j(a) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2} \sum_{i=1}^{N} (a - h_i)_+^{2(j-1)} - \hat{H}_j(a)^2\right], \qquad \text{H}=F_x, F_y \quad \text{and} \quad \text{h}=x, y,$$

$$\hat{V}_{x,y}^j(a) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2} \sum_{i=1}^{N} (a - x_i)_+^{j-1} (a - y_i)_+^{j-1} - \hat{F}_{xj}(a)\hat{F}_{yj}(a)\right].$$

In which $F_x$and F_y are defined in (1) and $(a)_+ = \max\{a, 0\}$.

It is empirically impossible to test the null hypothesis for the total support of the distributions. Thus, we test the null hypothesis for a preconceived finite number of values a. Specifically, the following hypotheses are tested:

H0: $F_{xj}(a_i) = F_{yj}(a_i)$ for alla_i, i=1, 2…, k, HA:$F_{xj}(a_i) \neq F_{yj}(a_i)$ for some a_i,

HA1:$F_{xj}(a_i) \leq F_{yj}(a_i)$for all$a_i$, $F_{xj}(a_i) < F_{yj}(a_i)$for some$a_i$,

HA2:$F_{xj}(a_i) \geq F_{yj}(a_i)$for all$a_i$, $F_{xj}(a_i) > F_{yj}(a_i)$for some$a_i$,

To control the probability of rejecting the null hypothesis, following Bishopet al. (1992) (BFT), we use the Studentized Maximum Modulus (SMM) distribution with m and infinite degrees of freedom, noted $\boldsymbol{M^k}_\infty$. The percentile 1-α of $\boldsymbol{M^k}_\infty$noted $\boldsymbol{M^k}_{\infty\boldsymbol{\alpha},}$, is tabulated by Stoline and Ury (1979) and the following decision rules are adopted:

if$|T_s(a_i)| < M^k{}_{\infty\alpha}$for i=1, …, k, 'accept H0';

if$T_s(a_i) < M^k{}_{\infty,\alpha}$ for all i et -$T_s(a_i) > M^k{}_{\infty,\alpha}$for some i, 'accept HA1' ;

if$-T_s(a_i) < M^k{}_{\infty,\alpha}$ for all i et $T_s(a_i) > M^k{}_{\infty,\alpha}$for some i, 'accept HA2' ;

if$T_s(a_i) > M^k{}_{\infty,\alpha}$for all i et --$T_s(a_i) > M^k{}_{\infty,\alpha}$for some i, 'accept HA' ;

The DD test compares the distributions at a finite number of grid points $\{a_k, k = 1,2 \dots, k\}$. The choice of these points is guided by the results of various studies**.** Tse and Zhang (2004) show that the appropriate choice of k for reasonably large samples is between 6 and 15. In this case, too few grids will miss information on the distributions between any two consecutive grids (Barrett and Donald (2003).

We note that in the above hypotheses, HA is excluded of both HA1 and HA2, which means that if either HA1 or HA2 is accepted, does not mean that HA is accepted. Accepting either H0 or HA implies that there are no SD relationships and no arbitrage opportunity between these two diversified portfolios and neither of these two portfolios is preferred to the other. However, if HA1 or HA2 is accepted in the first order, this shows that a P1 portfolio stochastically dominates a P2 portfolio at the first order. In this situation, there is an arbitrage opportunity and, as a result, investors can maximize their expected wealth if they move from the dominated portfolio to the dominant one. On the other hand, if HA1 or HA2 is accepted according to the 2nd or 3rd order, we say that P1 stochastically dominates P2 at the second or third order. In this situation, an arbitrage opportunity does not exist and the transition from one portfolio to another will only increase the expected utility of investors, but not their expected wealth Wong et al. (2008).

Result

Impact of the ESG criterion on the performance of portfolios before the crisis.

Table 1 below shows the distribution of our sample composed of 9 companies before the covid 19 crisis according to the intensity of the ESG score.

Low score ESG	Medium Score ESG	High Score ESG
SAFRAN THALES	SCHNEIDER ELECTRIC BOUYGUES	LEGRAND SAINT GOBAIN VINCI AIRBUS TELEPERFORMANCE

Table 1: Distribution Of Industrial Companies in the CAC40 Index According to the Intensity of the ESG Score Before the Crisis

- **GeneticAlgorithm**

By applying the genetic algorithm, we obtained the optimal portfolio weights for each company within the respective ESG-based groups, as presented in tables 2, 3 and 4 below.

Companies	**AIRBUS**	**VINCI**	**LEGRAND**	**SAINT GOBAIN**	**TELEPERFORMANCE**
W	0.0254	0.0683	0.08120	0.0259	0.7982
Average return =0.0094					
Variance =0.007					

Table2: The Optimal Weights of the Different Assets of the Portfolio P1 (High Score ESG)

Companies		**SCHNEIDER ELECTRIC**	**BOUYGUES**		
W		0.99	0.01		
Average return =0.0021					
Variance =0.0055					

Table3: The Optimal Weights of the Different Assets of the Portfolio P2 (Medium Score ESG)

Companies	**SAFRAN**	**THALES**			
W	0	1			
Average return =-0.101					
Variance =0.01					

Table4: The Optimal Weights of the Different Assets of the Portfolio P3 (Low Score ESG)

Figure 3 illustrates that the cumulative distribution functions of the portfolio pairs (P1, P2), (P1, P3), and (P2, P3) intersect in both sub-periods. This indicates the absence of first-order stochastic dominance (FSD) between any pair of portfolios.

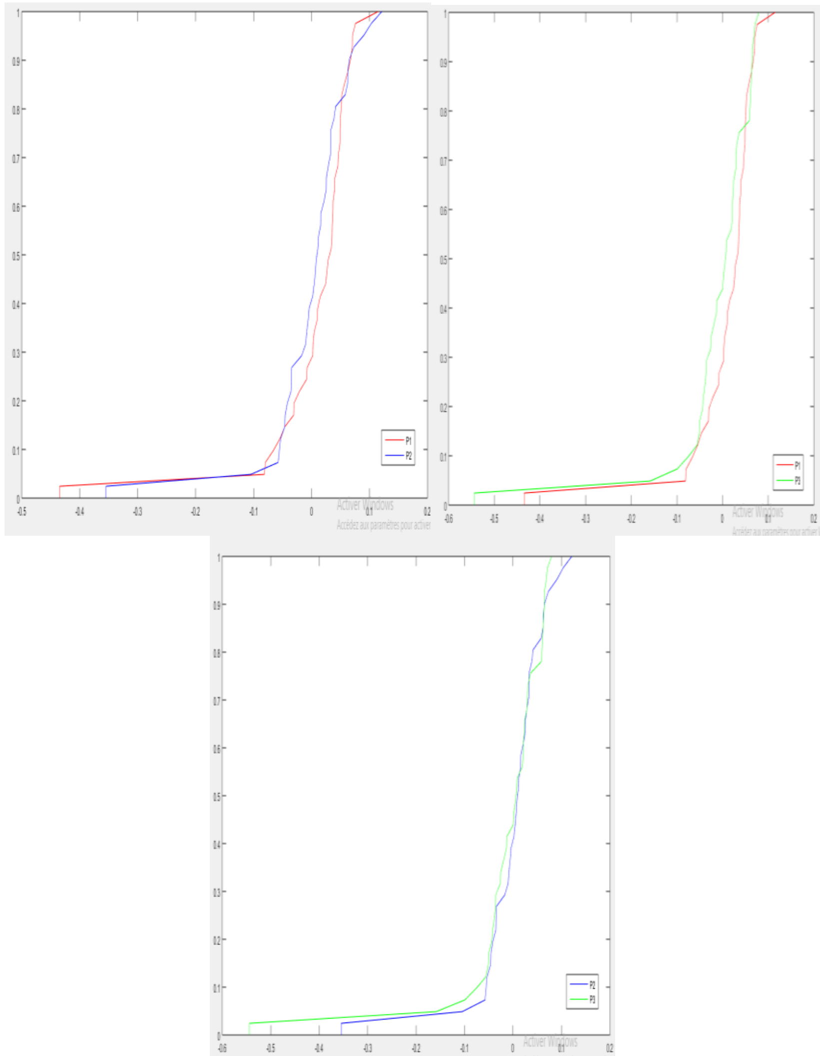

Figure 3

Plot of the cumulative distribution functions of the two portfolios (P1 P2), (P1,P3) and (P2,P3) before the crisis

Table 5 below presents the conclusions of the dominance tests carried out before the covid19 crisis. Indeed, Table 5 reveals the existence of a second and third order stochastic dominance between the portfolios. It was found that the portfolio composed of companies with a high ESG score (P1) dominates those composed of companies with a medium (P2) and low (P3) ESG score, according to the second and third order. Similarly, the P2 portfolio dominates the P3 portfolio. This proves that ESG performance has a positive impact on the performance of financial portfolios and offers an investment advantage.

Portfolio	**P1**	**P2**	**P3**
P1		$\succ^{2,3}$	$\succ^{2,3}$

P2	$\succ^{2,3}$
P3	

Table5: Stochastic Dominance Test Between P1, P2 And P3

Note: ≻ means that P1 dominates P2 and P3.[2,3]means SSD and TSD. The significance level of all our SD tests is the conventional one, which is 5%.

Impact of the ESG Criterion on the Performance of Portfolios During the Crisis.

Table 6 below shows the distribution of our sample composed of 9 companies during the crisis according to the intensity of the ESG score.

Low score ESG	Medium Score ESG	High Score ESG
SAFRAN THALES	SCHNEIDER ELECTRIC BOUYGUES	LEGRAND SAINT GOBAIN VINCI AIRBUS TELEPERFORMANCE

Table 6: Distribution of Industrial Companies in the CAC40 Index According to the Intensity Of The ESG Score During the Crisis

- **GeneticAlgorithm**

By applying the genetic algorithm, we obtained the optimal portfolio weights for each company within the respective ESG-based groups, as presented in tables 7, 8 and 9 below.

Companies	**AIRBUS**	**VINCI**	**LEGRAND**	**SAINT GOBAIN**	**TELEPERFORMANCE**
W	0.0384	0.0197	0.004	0.983	0.0006
Average return =0.032					
Variance =0.0092					

Table 7: The Optimal Weights of the Different Assets of the Portfolio P1 (High Score ESG)

Companies		**SCHNEIDER ELECTRIC**	**BOUYGUES**		
W		1	0		
Average return =0.0229					
Variance =0.0065					

Table 8: The Optimal Weights of the Different Assets of the Portfolio P2 (Medium Score ESG)

Companies	**SAFRAN**	**THALES**			
W	0.5032				

Belkhir et al. 1997

		0.4978			
Average return =0.0256					
Variance =0.0117					

Table 9: The Optimal Weights of the Different Assets of the Portfolio P3 (Low Score ESG)

- **Stochastic Dominance**

From figures 3 below, we see that the cumulative distribution functions of (P1, P2), (P1, P3) and (P2, P3) intersect for the two sub periods. It is therefore clear that there is no 1st order stochastic dominance (DS) between each peer.

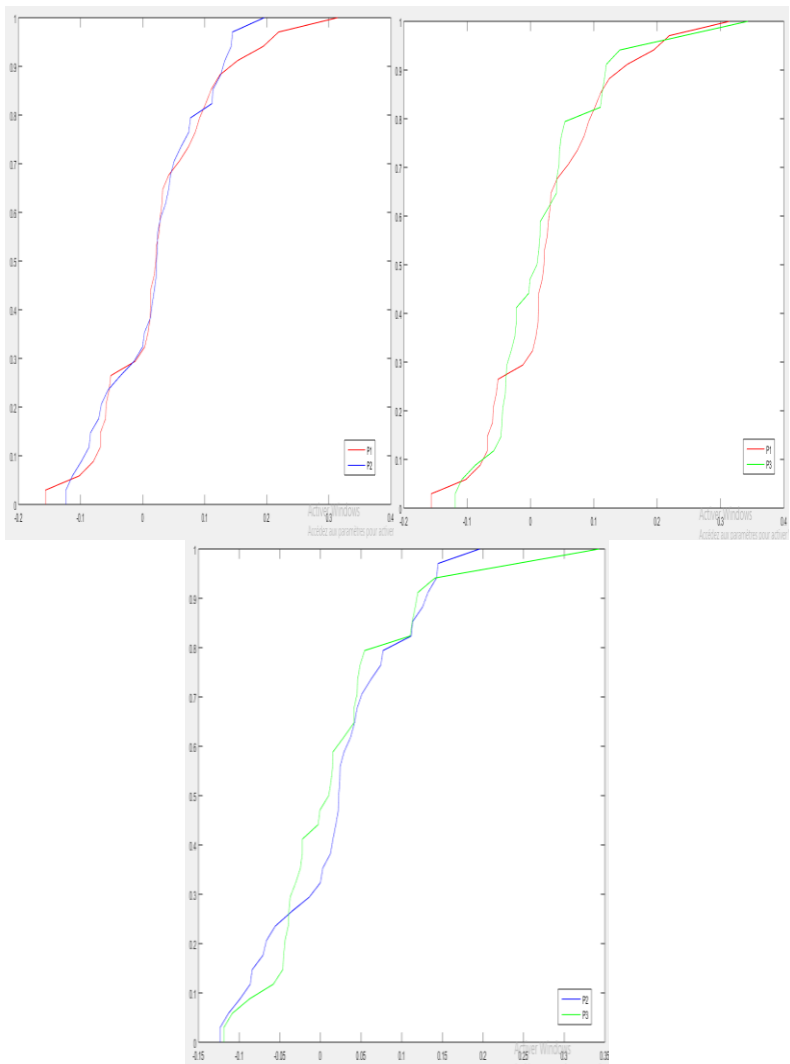

Figure 4: Plot Of The Cumulative Distribution Functions of the Two Portfolios (P1 P2), (P1,P3) And (P2,P3) During The Crisis

In contrast, the impact of ESG performance on financial performance was found to be insignificant during the period of significant turbulence observed at the start of the Covid-19 pandemic, particularly in March 2020, when the markets recorded their largest decline. The results from the stochastic dominance analysis indicate the absence of a clear dominance relationship between portfolios according to their ESG score level. It follows that ESG criteria do not appear to be a factor in the resilience of stock prices during a major health crisis. These conclusions are consistent with those of Dermes et al. (2021), who also highlight the loss of effectiveness of ESG criteria in the context of a systemic shock.

Portfolio	**P1**	**P2**	**P3**
P1		$\succ^{3}$	ND
P2			ND
P3			

Table 10: Stochastic Dominance Test Between P1, P2 And P3

Note: $\succ$ means that P1 dominates P2.^{2,3}means SSD and TSD. ND means that there is no SD. The significance level of all our SD tests is the conventional one, which is 5%.

Conclusion

We conducted a study to assess the impact of ESG scores on the financial performance of portfolios composed of French industrial companies included in the CAC 40 index, distinguishing between two periods: before and during the COVID-19 crisis. First, we used genetic algorithms to optimize three portfolios characterized by different ESG score levels (high, moderate, and low). Second, the stochastic dominance method was applied to compare the performance of these portfolios in a pairwise manner. The results indicate that before the crisis, a high ESG score was associated with better financial performance. However, this effect became insignificant during the sharp market decline observed in March 2020.

These findings have several implications for investors, portfolio managers, and policymakers. For investors, the study highlights the value of considering ESG scores as a relevant factor for asset selection in normal market conditions, but also the need to diversify valuation approaches in times of crisis. For managers, these findings suggest that a long-term view is needed to fully leverage the benefits of ESG practices, integrating upfront costs into an overall strategic perspective. Finally, for policymakers, the findings highlight the importance of strengthening regulatory frameworks and incentives to support ESG practices, particularly in times of crisis, to foster a sustainable transition even in volatile financial environments.

The environmental score is primarily based on three dimensions: waste management, greenhouse gas emissions, and energy consumption. Greater efficiency in these areas can lead to long-term cost reductions, which can boost financial performance. However, the investments required to implement responsible environmental practices can generate significant short-term costs, making their positive effects more visible over the long term. The social score encompasses aspects related to employee well-being and consumer satisfaction. A favorable work environment generally increases productivity, while a good customer reputation can strengthen loyalty and boost sales, thus contributing to the company's overall performance. Finally, the governance score covers elements such as board structure and diversity, transparency in executive compensation, and the fight against corruption. Effective governance promotes better strategic decision-making and reduces operational risks, which can improve financial performance. The lack of a significant relationship between ESG scores and financial performance during the health crisis could be explained by the lack of a structural and stable correlation between non-financial performance and stock market performance in the context of a major exogenous shock. In other words, ESG criteria, although important in normal times, seem to have been eclipsed by market dynamics dominated by macroeconomic and health factors during this exceptional period.

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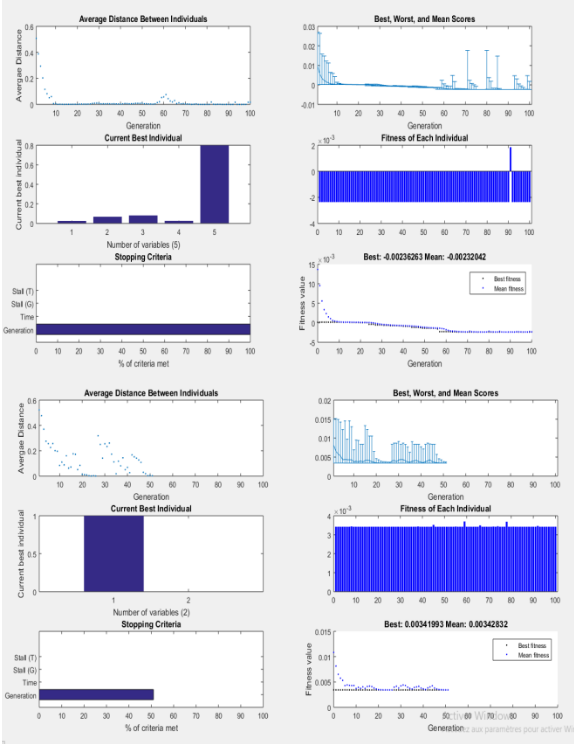
Annex

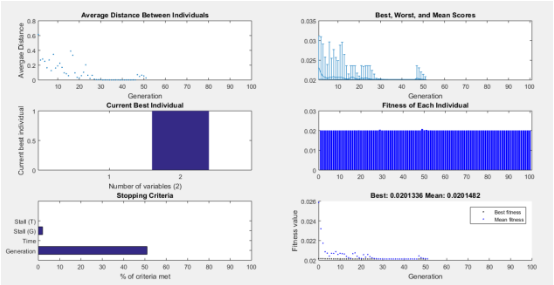
GENETIC ALGORITHM

Before CRISE

P1 **P2**

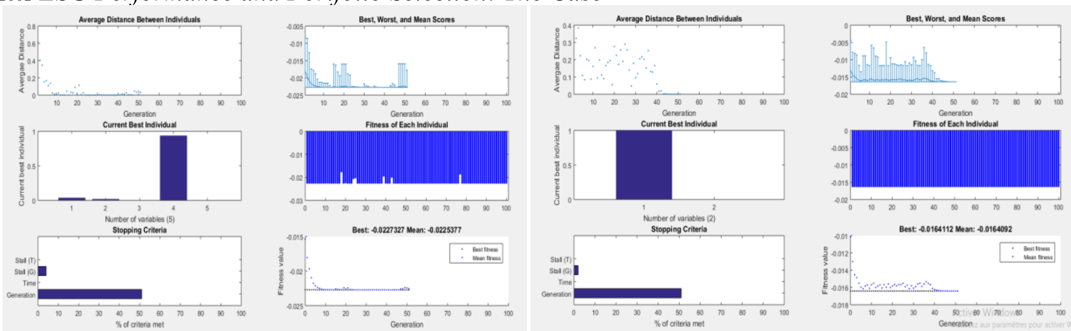


P3

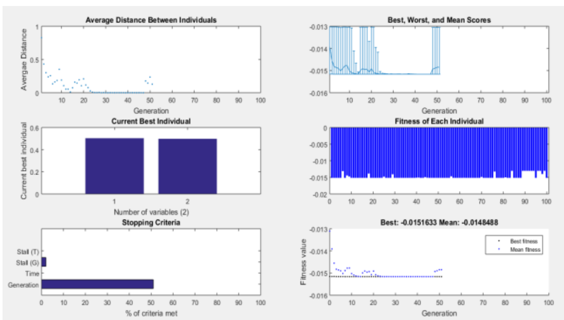


During crisis

P1 **P2**



P3



- Competing interests

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

- Ethics statement

We declare that this manuscript is not currently being considered for publication elsewhere. We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property.
We declare that this article does not contain any studies with human participants or animals performed by any of the authors.