# A two-level portfolio model based on expected values of corporate social responsibility

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**Abstract.** Modern economic theory believes that enterprises, one of the stock issuers in the financial market, serve as a fundamental "mechanism for resource allocation". The theory also holds that the mechanism can achieve the optimal allocation of the entire economic resources while simultaneously reducing the "transaction costs" of the entire society. However, the shortsightedness and profit-seeking nature of enterprises lead to enormous issues with economic development. These issues include excessive consumption of resources, continuous accumulation of industrial pollution, and the deteriorating ecological environment, triggering a series of social, environmental, and economic problems. Hence, solving the contradiction between economic growth and environmental protection, and achieving sustainable economic and social development has become an urgent problem to be solved. Corporate social responsibility receives increasing attention nowadays, and more and more scholars are carrying out their research. The present research constructs a multi-level portfolio model based on expected values of corporate social responsibility. In particular, the research utilizes the stock returns and corporate social responsibility performance of Chinese listed companies to analyze the relationship between them. The research shows that the stock returns of Chinese-listed companies are negatively correlated with their social responsibilities.

**Keywords:** corporate social responsibility, portfolio, expected value, multi-level model

## 1 Introduction

The continuous improvement of environmental protection awareness leads to investors being increasingly concerned about their fulfillment of corporate social, environmental, and economic responsibilities. Corporate social responsibility, in particular, is also increasingly influencing investors' investment decisions [1]. A company defaulting on


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employee salaries, evading taxes, polluting the environment, deceiving customers, and committing financial fraud seriously damages its own image and reputation. In addition, the capital market quickly reacts negatively to the offending company, and the major social, economic, and environmental issues from the offense often come with a series of fines, compensation, and litigation. The negative impact of the offense is also on the production and operation activities of the enterprise in the long run. This negative impact in turn affects the investors' expected judgments and investment decisions on the future earnings of the enterprise, seriously affecting the value of the enterprise [2].

Scholars of corporate social responsibility research are mainly studying the relationship between corporate social responsibility and the stock market or the market performance of social responsibility investments. Many studies have shown that there is a very complex relationship between social responsibility and corporate performance. Notably, the excess return of asset portfolios that follow social responsibility investment strategies is lower than that of traditional asset portfolios, as seen in developed countries in Europe and America. This observation indicates that social responsibility has a hedging effect on stock returns. Investors also bear greater risks due to poor corporate image out of the lack of social responsibility, requiring companies to provide higher returns.

The decision-making system of an actual investment process is hierarchical. Decision makers are often not one in the system, and the multiple decision makers include a leader and several subordinates [3]. Decision makers and their subordinates have their own decision variables and objective functions. Decision makers can influence their subordinates through their decisions. The subordinates also have sufficient authority to make decisions towards their respective goals. These decisions will in turn have an impact on the leaders and subordinates of the decision maker.

The above analysis shows that, with the rapid development of the capital market and the rapid growth of total capital, institutional and individual investors are increasingly aware of the importance of corporate social responsibility for sustainable development. It is necessary to achieve this sustainable investment through certain methods, strategies, or theoretical models, while achieving investment returns and avoiding risks. One example of this achievement is that the factors of social responsibility are taken into consideration in asset allocation for sustainable development. As of now, the research of Chinese scholars on corporate social responsibility is relatively small compared to that of European and American scholars.

Therefore, this research constructs a multi-level corporate social responsibility portfolio model from the perspective of investors. The research uses data from the Shanghai and Shenzhen stock markets and corporate social responsibility data from relevant research institutions. Subsequently, we analyze the impact of the social responsibility of Chinese-listed companies on portfolios. The above model assumes that the leader focuses on the financial returns of the portfolio and its ratio to social responsibility. Another assumption is that each subordinate is responsible for achieving the corporate social responsibility indicators of the portfolio.

## 2 Multi-level planning

Multi-level programming was first proposed by scholars, such as Jerome et al.[5], in 1974. The objective of this programming was to construct a distributed non-cooperative decision-making system with one leader and multiple subordinates of the same level. Multi-level programming is used to study distributed decision-making problems. The leaders and their subordinates in this programming have their own decision variables and objective functions. Leaders make decisions that affect their subordinates. At the same time, subordinates can make decisions towards their respective goals. These decisions in turn affect the leaders and subordinates of the decision maker. Multi-level programming is widely used in strategic planning [3], resource allocation [4], and other fields. Ben and other scholars [6] proved that the multi-level planning problem is a NP problem through the Knapsack problem in 1990. Scholars have also proposed algorithms to solve the multi-level planning problem. Some of these algorithms include the extreme point method [7], k-order optimal method [8], branch and bound method [9], fastest descent method [10], and intelligent algorithm [11]. Generally, the parameters of multi-level planning are uncertain in many cases. So, Patriksson and other scholars [12] proposed a multi-level planning model under probability measure for the first time. In addition, Gao et al. [13] proposed some stochastic multi-level programming models, and Lai [14] proposed a multi-level programming model under fuzzy measures for the first time. Based on these two studies, Shih et al. [15] and Lee [16] further studied fuzzy multi-level programming problems. It is worth mentioning that Gao et al. [17] proposed a fuzzy multi-level programming model with a Nash equilibrium solution. Likewise, Liu et al. [18] constructed a multi-level programming model under uncertainty measures. Finally, Woldemariam et al. [19] proposed an evolutionary algorithm considering bounded decision variables for nonlinear, nonconvex, and nondifferentiable irregular multi-level programming problems.

This research considers a decision system with a two-layer structure. Suppose there is a decision maker and m subordinates. Then, x and yi are the decision vectors of the leader and the i subordinate, respectively. Likewise, F (x, y1, y2， ..., ym) and fi (x, y1, y2， ..., ym) are the objective functions of the leader and the i subordinate (with i=1,2, …, m), respectively.

Let S represent the feasible set of decision variables for decision makers,

$$S = \{x | G(x) \leq 0\} \tag{1}$$

Amid this formula, G is a vector-valued function for decision-making, and 0 represents a zero-valued vector, that is, all elements of the vector are zero. For each decision x chosen by the leader, the control variable of the $i$ subordinate not only depends on $x$, but also on the influence of y1, y2， ..., ym. Therefore, for the i subordinate, there is a constraint condition $g_i(x, y_1, y_2, \ldots, y_m) \leq 0$, where $g_i$ is a vector function ($i = 1,2, \ldots, m$).

Assume that the leader first selects decisions within their feasible set, and their subordinates make corresponding decisions based on these decisions by the leader. This research constructs a two-level programming model for simplicity as shown below.

$$\begin{cases} \max\limits_{x} F(x, y_1, y_2, \ldots, y_m) \\ s.t. \quad G(x) \leq 0 \\ \\ \quad \begin{cases} \max\limits_{x} \ f_i(x, y_1, y_2, \ldots, y_m) \\ s.t. \quad g_i(x, y_1, y_2, \ldots, y_m) \leq 0 \quad (i = 1, 2, \ldots, m) \end{cases} \end{cases} \tag{2}$$

For each decision $x$, the Nash equilibrium of subordinates is defined as . Also, for any $(y_1, \ldots, y_{i-1}, y_i, y_{i+1}, \ldots, y_m) \in Y(x)(i = 1,2, \ldots, m)$, it holds.

$$f_i(x, y_1, \ldots, y_{i-1}, y_i, y_{i+1}, \ldots, y_m) \leq f_i(x, y_1^*, \ldots, y_{i-1}^*, y_i^*, y_{i+1}^*, \ldots, y_m^*) \tag{3}$$

Let $x^*$ be a feasible decision vector and $(y_1^*, , y_2^*, \ldots, y_m^*)$ be a corresponding Nash equilibrium. Then, call sequence $(x^*, y_1^*, , y_2^*, \ldots, y_m^*)$ a Nash equilibrium solution of bi-level programming (P1) if and only if the following inequality holds for any $\overline{x} \in S$ and its corresponding Nash equilibrium solution $(\overline{y_1}, \overline{y_2}, \ldots, \overline{y_m})$.

$$F(\overline{x}, , \overline{y_1}, \overline{y_2}, \ldots, \overline{y_m}) \leq F(x^*, y_1^*, , y_2^*, \ldots, y_m^*) \tag{4}$$

# 3 Expected Value of Two-Level Portfolio Model

## 3.1 Model construction

An expected value model is a mathematical programming that achieves the optimal expected value of the objective function under constraints. The expected value operator plays an extremely important role in probability theory and is one of the most common forms of stochastic programming. Some applications of this programming are in solving the problem of minimizing expected cost, the problem of maximizing expected benefit, etc. In this research, we use the expected value model and the multi-level hierarchical model to construct a random expected value multi-level portfolio model considering social responsibility, as shown below.

$$
(P2)\begin{cases}
\max \quad E\left[\dfrac{\sum_{i=1}^{N} x_i r_i}{\sum_{i=1}^{N} x_i MR_i + \sum_{i=1}^{N} x_i MR_i' + \sum_{i=1}^{N} x_i SR_i + \sum_{i=1}^{N} x_i ER_i}\right] \\
0 \le x_i \le 1 \quad i = 1,2,\ldots,N \\
\sum_{i=1}^{N} x_i = 1 \\
\sum_{i=1}^{N} x_i \sigma_{ij} x_j \le R \\
\begin{cases}
\max \quad E[\sum_{i=1}^{N} x_i R_i] \\
0 \le x_i \le 1 \quad i = 1,2,\ldots,N \\
\sum_{i=1}^{N} x_i = 1
\end{cases} \\
\begin{cases}
\max \quad E[\sum_{i=1}^{N} x_i MR_i] \\
0 \le x_i \le 1 \quad i = 1,2,\ldots,N \\
\sum_{i=1}^{N} x_i = 1
\end{cases} \\
\begin{cases}
\max \quad E[\sum_{i=1}^{N} x_i MR_i'] \\
0 \le x_i \le 1 \quad i = 1,2,\ldots,N \\
\sum_{i=1}^{N} x_i = 1
\end{cases} \\
\begin{cases}
\max \quad E[\sum_{i=1}^{N} x_i SR_i] \\
0 \le x_i \le 1 \quad i = 1,2,\ldots,N \\
\sum_{i=1}^{N} x_i = 1
\end{cases} \\
\begin{cases}
\max \quad E[\sum_{i=1}^{N} x_i ER_i] \\
0 \le x_i \le 1 \quad i = 1,2,\ldots,N \\
\sum_{i=1}^{N} x_i = 1
\end{cases}
\end{cases}
$$

In the above equation, $r_i$, $MR_i$, $MR_i'$, $SR_i$, $ER_i$, $R$ and $\sigma_{ij}$ are the return rate, management responsibility index, market responsibility index, social responsibility index, environmental responsibility index, the upper limit value of portfolio risk, and covariance between the $i$ security and the $j$ security, respectively $(i,j = 1,2,\ldots,N)$. The objective function of the first-level leader is the expected value of the portfolio return divided by the sum of four social responsibility indices. This objective function represents the return corresponding to the unit social responsibility index. The objective functions of the five subordinates in the second layer are the expected returns of the portfolio and the expected values of the four social responsibility indices.

The artificial neural network genetic algorithm proposed by Liu [18] is used to solve this model, and the specific steps of the algorithm are as follows.

Step 1: Set parameters such as population size, number of iterations, crossover probability, and mutation probability.

Step 2: Initialize chromosomes in the feasible domain.

Step 3: Use genetic algorithms and neural networks to simulate and calculate the Nash equilibrium between leaders and subordinates.

Step 4: Calculate the Nash equilibrium objective function value of the leader in each chromosome.

Step 5: Calculate the fitness of each chromosome based on the objective function value.

Step 6: Randomly select chromosomes as offspring for the next iteration based on the roulette wheel operator.

Step 7: Repeat steps 2 to 6 until the given number of iterations.

Step 8: Output the optimal chromosome as the optimal solution.

### 3.2 Empirical Analysis

This paper uses data from the Center for Social Responsibility Research at the University of Chinese Academy of Social Sciences [20] and Wind [21] for empirical analysis. Six stocks are selected from the Shanghai and Shenzhen stock markets in China randomly, and their returns and CSR indices are shown in Table 1.

**Table 1.** Annualized Financial Returns and Annual CSR Index of Six Stocks

| No | Stock code | Annualized return | Management responsibility | Market responsibility | Social responsibility | Environmental responsibility |
|---|---|---|---|---|---|---|
| 1 | 600428 | 0.0310 | 88.5250 | 57.1250 | 89.1000 | 77.4750 |
| 2 | 000534 | 0.0007 | 79.8750 | 66.4000 | 65.7500 | 77.3000 |
| 3 | 600505 | 0.0068 | 79.8750 | 66.4000 | 65.7500 | 77.3000 |
| 4 | 000539 | 0.0010 | 79.8750 | 66.4000 | 65.7500 | 77.3000 |
| 5 | 600797 | 0.0067 | 79.8750 | 66.4000 | 65.7500 | 77.3000 |
| 6 | 600726 | 0.0238 | 68.3750 | 56.8250 | 58.2500 | 62.8250 |

This research studies the changes in the objective function values of the model by changing various parameters in the genetic algorithm. The objective of this study is to verify the robustness and effectiveness of the genetic algorithm in the above model and analyze the relationship between the two decision variables in the model. In Table 2, $NO$ represents the sequence number of the solution, $GN$ represents the number of iterations, $Size$represents the number of populations, $P_c$ represents the crossover rate, and $P_m$represents the mutation rate.

**Table 2.** Solution of P2 Model

| NO | GN | Size | Pc | Pm | Nash equilibrium | Objective function value | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Leader | S1 | S2 | S3 | S4 | S5 |
| 1 | 500 | 100 | 0.9 | 0.3 | (0.5397,0.3292,0.0, 0.1251,0.0,0.0059) | 0.03 | 0.0172 | 84.475 | 61.3373 | 78.3074 | 77.3085 |
| 2 | 1500 | 100 | 0.9 | 0.3 | (0.5538,0.3331,0.0, 0.1130,0.0,0.0001) | 0.0302 | 0.0175 | 84.6633 | 61.2624 | 78.6792 | 77.3947 |
| 3 | 2500 | 100 | 0.9 | 0.3 | (0.7679,0.1093,0.0, 0.1221,0.0,0.0007) | 0.0305 | 0.024 | 86.5093 | 59.2714 | 83.6748 | 77.4245 |
| 4 | 500 | 100 | 0.3 | 0.3 | (0.3173,0.4637,0.0, 0.1933,0.0,0.0256) | 0.0294 | 0.011 | 82.3228 | 63.2107 | 72.9642 | 76.983 |
| 5 | 1500 | 100 | 0.3 | 0.3 | (0.3802,0.6193,0.0, 0.0004,0.0,0.0001) | 0.0296 | 0.0122 | 83.1629 | 62.873 | 74.627 | 77.3655 |
| 6 | 2500 | 100 | 0.3 | 0.3 | (0.4721,0.5271,0.0, 0.0008,0.0,0.0) | 0.0298 | 0.015 | 83.9583 | 62.021 | 76.7733 | 77.3823 |
| 7 | 1500 | 100 | 0.3 | 0.1 | (0.5270,0.2681,0.0, 0.0525,0.0,0.1524) | 0.0293 | 0.0202 | 82.6803 | 60.0525 | 76.9118 | 75.1855 |
| 8 | 1500 | 300 | 0.3 | 0.1 | (0.8648,0.0332,0.0, 0.1018,0.0,0.0001) | 0.0307 | 0.0270 | 87.348 | 58.3732 | 85.9367 | 77.444 |
| 9 | 1500 | 500 | 0.3 | 0.1 | (0.9742,0.0167,0.0, 0.0091,0.0,0.0) | 0.031 | 0.0303 | 88.3015 | 57.3641 | 88.4973 | 77.4702 |

It can be observed from Table 2 that the optimal objective function value of the leader is positively correlated with the population size, iteration number, crossover rate, and mutation rate of the genetic algorithm in the solution of P2. However, the correlation between the optimal objective function values of each subordinate and the population size, iteration times, crossover rate, and mutation rate of the genetic algorithm is uncertain. The implementation of the leader's objective function comes at the cost of sacrificing the objective functions of some subordinates. At the same time, the objective functions of other subordinates are optimized to some extent.

## 4 Conclusions

This research uses multi-level programming theory to construct a multi-level investment portfolio model based on the expected values of corporate social responsibility. The ratio of financial returns to four social responsibility indices is used as the first-level objective function. Further, financial returns and four social responsibility indices are used as the five sub-objective functions of the second level. Among these objective functions, the two-level objective functions of the multi-hierarchical database model of expected value are expected value operators. Then, genetic algorithms and neural networks are used to solve the Nash equilibrium between leaders and subordinates. Finally, an empirical study was conducted using the yield data of China's Shanghai and Shenzhen stock markets and the social responsibility index of domestic listed companies.

This research has shown that the improvement of the first layer objective function in this model is at the cost of sacrificing certain objective functions in the second layer. At the same time, the other objective functions of the second layer have also been improved with the improvement of the first layer objective function. This observation indicates that the financial returns of Chinese-listed companies are negatively correlated with their social responsibility. In light of recent developments, it is imperative for China to reconsider its approach to economic development, which has often involved making sacrifices in other areas. Moreover, the expected value multi-level investment portfolio model demonstrates remarkable robustness, making it a promising avenue for exploration. Meanwhile, it has been observed that the values of the first-layer objective function, along with certain second-layer objective functions, exhibit a positive correlation with critical factors such as the population size, iteration times, crossover rate, and mutation rate of the intelligent algorithm.

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