



# Combining VIKOR-DANP model for glamor stock selection and stock performance improvement



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## ABSTRACT

This study proposes a multiple attributes decision making (MADM) method for solving glamor stock selection problem based on fundamental analysis. Traditional analyzes rely on choosing key financial ratios in making comparison, or by observing the trends of change in various financial variables (also termed as criteria or signals in this study). However, most of the criteria for stock selection have inter-dependent/interactive characteristics. In practice, investors often have to make compromising decisions when target stocks indicate conflicting performance outcomes in different criteria. Traditional methods have difficulty in making decision while facing inter-dependent criteria and compromise alternatives. Thus, this study proposes a combined MADM method to retrieve financial experts' knowledge for glamor stock selection. The proposed method not only helps to identify the ideal glamor stock, but the pertaining insights may also be used for the management teams of glamor stocks to prioritize their improvement plans. In addition, this study provides an empirical case in analyzing five glamor stocks of semiconductor industry in Taiwan. The result indicates that the proposed method for glamor stock selection is effective and provides meaningful implications for investors and management teams to refer. The selected top ranking stock consistently outperformed the other four glamor stocks in 32 month and 44 month holding periods from May 2009 to December 2012 with statistical significance, which indicated the effectiveness of the proposed model.

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## 1. Introduction

In this study, we aim to propose a combined multiple attributes decision making (MADM) method to deal with the glamor stock selection problem, which has caused increasing interest in both academic and practical fields [1]. The stock selection problem was stemmed from the efficient market hypothesis (EMH), and it could be traced back to the original work of efficient capital markets [2]. From the assumption of EMH, investors cannot use available information to formulate a strategy that consistently outperforms the market [3–5]. To examine the EMH, some previous studies tended to apply various investing styles to test the hypothesis. Value investing and growth stock (also termed as glamor stock in financial literature) investing are two of the commonly examined strategies [6,7]. These two investing strategies

use simple valuation criteria separately to form different investment portfolios. The value stock portfolio was found to outperform the diversified portfolio or market index in the long-term [7], which has gathered attention from both academic and practical fields. But the emerging recognition towards growth stock investing strategy also caught investors' interests in practice. From the definition of previous study [8], glamor stocks are expected by market to perform well in the future, embracing relatively low B/M (book to market value) or E/P (earning to price) ratio. Although the discussion of growth stock investing in academic research has formed a foundation for investment practice [9], while making real investment decision, investors still have to make selection among the growth stock portfolio because of limited capital constraint. In making stock selection, fundamental analysis (FA) is a main approach in evaluating a stock for its financial worthiness by using historical data [10]. However, relatively little attention has been given to the use of FA for glamor stock investment. Thus, this study focuses on examining the proposed model as a basis for glamor stock selection, and provides directions for the management teams of glamor stocks to improve their stock performance.

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Some previous attempts in applying quantitative models were conducted to predict stock performance by using financial data. On one hand, the artificial intelligence (AI) approach is broadly applied, such as the artificial neural network (ANN) technique often uses financial data as input variables to predict future stock performance [11–13]. To retrieve rules for stock price prediction, integrated fuzzy system and ANN was also introduced [14]. Despite the superior modeling capability of the ANN, the black-box processing characteristic often impedes the way to gain insights of the influential effects for investors to comprehend. On the other hand, the multiple attributes decision-making (MADM) approach has been considered to solve the stock selection problem recently. One of the mainstreams is the data envelopment analysis (DEA) approach, which has gained research interests for the portfolio selection problem [15]. Although the DEA method seems to provide a useful tool for portfolio selection, it still lacks of capability to explore the relationships among financial variables for more in-depth analysis. In order to help fill the gap, this study proposes a combined MADM model to solve the glamor stock selection problem, aiming at exploring the plausible interrelationships among the considered criteria for making better decision.

The main concern of glamor stocks is that they are relatively expensive, if the glamor stocks fail to maintain the market's confidence, it often leads to significant price corrections. Thus, the glamor stocks selection is more challenging compared with the generic stock selection problem. Research has shown that stock market tends to naively extrapolate recent fundamentals of glamor stocks [16], which attributed to cognitive biases [6]. To consider the “naïve extrapolation” effect of growth stock investing, Mohanram [1] included this dimension (naïve extrapolation) in his proposed G-score model with the other financial criteria. In this study, we follow the conceptual framework of the traditional G-score model to regard “naïve extrapolation” as a major dimension for glamor stock selection. Although the findings of the G-score model contributed to identify relevant financial information regarding growth stock investing, the model chose a simplified approach to transform relevant financial information into binary inputs, and formed a logistic regression model to separate gainers from losers. In the regression model of the G-score, dependent variables were set to be either one or zero, comparing a firm's financial ratios with its contemporary industry average as signals. Although the G-score model showed the possibility to use FA for growth stock investing, it still has some limitations and potential drawbacks.

To improve the limitations of previous studies [1,10–13], this study proposes a combined MADM model for four advantages. Firstly, the designed transformation of performance scores for each stock in different criteria (see Section 4) may measure the relative strength of each stock more adequately. The traditional G-score model cannot measure the distance of a stock's current performance with its industry average in each criterion. The extreme values cannot be reflected in a proportional manner. For example, suppose the average ROA (return over total asset) of the electronic industry is 1%, and the current ROA of Stock A and B are 19% and 4% respectively. In the G-score model, both of the two stocks' ROA signals will be set to one; but in reality, the Stock A's ROA is about five times better than the Stock B's result. In our proposed model, this drawback can be overcome by measuring the distance between the aspired/ideal level and current status of financial variables for each stock. Secondly, the logistic regression model adopted by previous research [1] assumed that variables are independent, which is not realistic in practice. The proposed Decision-Making Trial and Evaluation Laboratory (DEMATEL) method applied in this study may preserve the interrelationships among financial variables/criteria, which could be used to adjust the influential weights based on the basic concept of the analytical network process (ANP), termed

as the DANP (DEMATEL-based ANP) in this study [17]. Thirdly, the proposed model can decompose criteria into cause and effect groups for gaining more insights. Compared with previous studies that used the DEA or the ANN technique [10–13], the proposed model can explore the interrelationships among criteria, provides more information for management teams to make strategic plans. Lastly, the integration of VIKOR method can provide the priority of improvement gaps for growth stocks, which may be regarded as a managerial tool to probe the direction for improvement to increase growth stocks' market value.

The rest of the study is organized as follows: in Section 2, this research reviews the concept of FA and growth stock investing. Also, some related MADM methods for solving the stock selection problem are introduced, including DEMATEL, DANP and VIKOR that are applied in the proposed model. In Section 3, a combined MADM framework is proposed for solving the stock selection problem. Section 4 provides an empirical example to rank the five selected glamor stocks and compare their stock performance with the output that our model suggests. Section 5 discusses the interrelationships of the evaluated dimensions and criteria, and provides implications to conclude this study.

## 2. Preliminaries

This section briefly reviews the concepts adopted by the research, such as FA, growth stock investing and related MADM methods for the stock selection problem.

### 2.1. Fundamental analysis

Traditionally, FA approach aims to focus on exploring the usefulness of financial statement analysis in predicting future earnings or returns. Piotroski [18] demonstrates the possibility to distinguish gainers from losers for value stocks by taking the FA approach. Another research thread follows this idea indicating that institutional investors and analysts have relatively more financial knowledge, rely more heavily on useful financial information for stock selection and evaluation. Such an approach tries to analyze how professional investors process relevant financial information and extrapolate a stock's fundamentals to conduct evaluation. This approach involves industry-specific and firm-specific factors in order to recognize the underlying value of a stock [19]. In the context of FA, this study proposes a combined MADM model to process relevant financial information from domain experts' knowledge.

### 2.2. Growth stock investing and the G-score model

By the definition from Lakonishok et al. [8], while investors get overly excited about stocks that have done very well in the past with growth tendency, investors' enthusiastic buy-in might cause these stocks to be overpriced. These stocks are named as “growth stock” or “glamor stock”, and they have relatively low B/M, E/P, or C/P ratios in their industry. Mohanram [1] developed the G-score model with three dimensions for growth stock investing. Firstly, the use of FA for glamor stock may start from examining profitability, such as ROA and cash flow profitability ratios. However, the use of profitability measurement might not be enough to explain the expensive valuation of glamor stocks. Some of the previous studies attributed the relatively high valuation to cognitive biases [1] of investors, stock market tends to naïvely extrapolate recent fundamentals overly for glamor stocks [16]. In the context of cognitive biases discussed above, the G-score model included “naïve extrapolation” as the second influential dimension. The third dimension addresses accounting conservatism [20], which pointed out the implications of conservative accounting

for future earnings, such as R&D expenses. The relevance of R&D expenses and future earning's performance was confirmed by previous study [21]. Chan et al. [22] also found that advertising expenses are associated with excess returns in future periods. In this study, we adopt the conceptual framework of the G-score model for glamor stock investing by the three mentioned dimensions and the extended criteria as Fig. 1.

### 2.3. Related MADM methods for stock selection problem

The stock selection problem is evaluated by multiple attributes (criteria) in practice, which is suitable to be examined through MADM approach. For instance, Lee et al. [23] used the ANP technique to explore stock selection based on Gordon model. The ANP (Saaty, 1996) [24] was developed from the analytical hierarchical process (AHP) to allow for interdependence among considered criteria. The ANP decomposes problem into clusters, and each cluster contains multiple variables/criteria for evaluation. To improve the equal weighting assumption of the traditional ANP method, the DEMATEL technique was introduced to combine with the basic concept of the ANP for solving complicated problems in influential weights, called the DANP (DEMATEL-based ANP) [17]. The DEMATEL approach was widely applied to various application fields in practice, such as the marketing strategy [25], the selection of outsourcing providers [26], and the portfolio selection based on CAPM [27]. The last MADM method discussed in this section is the VIKOR, which is applied to tackle the compromised ranking problem based on integrating/fusing gaps. The VIKOR technique introduces the multi-criteria ranking index based on the measurement of the closeness to the ideal/aspired level, which has advantage on ranking and selection from a set of alternatives in the presence of conflicting criteria [28]. Also, we can shift from ranking and selection when determining the most preferable approach to performance improvement based on influential network relation map (INRM) by the DEMATEL technique. The selection from a group of glamor stocks might often encounter conflicting performance outcomes in different criteria. The inclusion of VIKOR method based on INRM is probed and expected for how to reduce gaps among interdependent criteria for enhancing the decision outcome. To combine the VIKOR method with the influential weights of DANP (called VIKOR-DANP model), not only the top ranked glamor stock may be selected, but also the suggested priority for improving gaps in each criterion for the glamor stock could be derived for performance improvement.

### 3. Constructing the combined VIKOR-DANP model

This section introduces the conceptual framework of the G-score model for growth stock investing and the proposed hybrid methods, including DEMATEL technique (to form the relationship-structure model), DANP (find out influential weights for criteria with dependence and feedbacks from DEMATEL technique using the basic concept of ANP) (see Appendix A Stage1), and VIKOR (to form ranking scores and explore priority to reduce gaps for achieving the aspired level) (see Appendix A Stage2).

#### 3.1. Influential dimensions and sub-factors/criteria for DANP

The purpose of this study is to select glamor stocks with better financial prospects by using an integrated VIKOR-DANP model to improve the original G-score model. According to the design of the original G-score model, to evaluate a glamor stock's financial prospect can be divided into three dimensions: Earning and Cash Flow Profitability ( $D_1$ ), Naïve Extrapolation ( $D_2$ ), and Accounting Conservatism ( $D_3$ ). The three dimensions have their own two to three extended sub-factors. The overall structure is shown in Fig. 1.

The G-score model is a straightforward design, which measures the positive/negative signals of each criterion, comparing various indicators with the same industry's average ratios. And the explanation for each criterion may be found in Table 1. In the G-score model's original setting, signals are designed to be one/zero as positive/negative signals respectively. The total summed score is the model's single output. Each signal generated from a logistic regression model was considered as an independent variable, but the interrelation between each variable was ignored. In this study, we modified the signals from binary into ratio scale, which measures the difference between the ratio of individual stock and its industry average.

Besides, we suggest that each variable/criterion should not be treated independently because variables are often interrelated. For example, the change in profit ratio (such as ROA) is correlated to the change in accounting conservatism. Under the same profit structure, increase in R&D expense or capital expense will lead to decrease in ROA. The above example explains the limitation of the G-score model. To improve the original model, we used the VIKOR-DANP model to measure ratio scale of each financial indicator and reserve the interrelationships among criteria.

The VIKOR method is introduced because of the nature of investment decision. While facing a complex investment decision considering multiple criteria, alternatives often reveal inconsistent performance in different criteria. Decision makers often have to

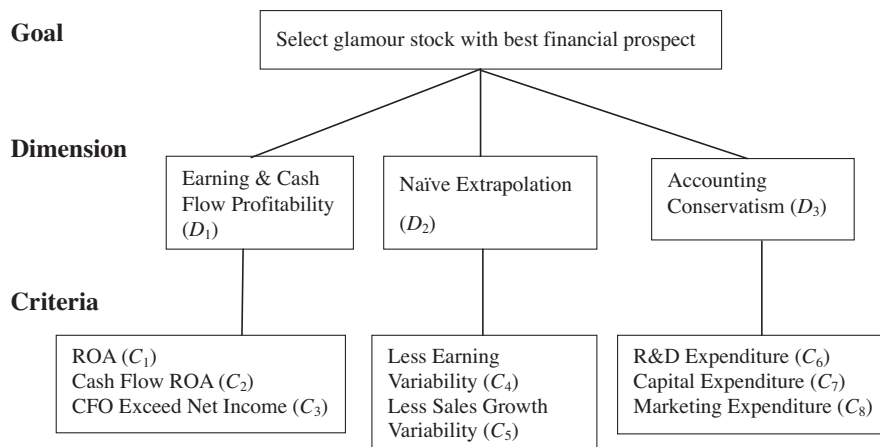


Fig. 1. The Structure of G-score model.

**Table 1**  
The influential dimensions and criteria of the glamor stock selection (G-score) model.

Dimensions	Influence criteria	Statements of influence criteria
Earning and cash flow profitability ( $D_1$ )	ROA ( $C_1$ )	Net income scaled by average assets
	Cash flow ROA ( $C_2$ )	Cash flow ROA is cash from operations scaled by average assets
	CFO exceed net income ( $C_3$ )	Cash flow from operation minus net income and scaled by average assets
Naïve extrapolation ( $D_2$ )	Less earning variability ( $C_4$ )	Standard deviation (SD) of quarterly earnings in previous 4 years (i.e., 16 quarters)
	Less sales growth variability ( $C_5$ )	Standard deviation (SD) of monthly sales growth in the previous 4 years (i.e., 48 months)
Accounting conservatism ( $D_3$ )	R&D expenditure ( $C_6$ )	R&D expense scaled by total assets
	Capital expenditure ( $C_7$ )	Capital expenditure scaled by total assets (capital expenditure is measured by net fixed-assets in the current year minus net fixed-assets in the previous year plus depreciation expenses in the current year)
	Marketing expenditure ( $C_8$ )	Marketing expenses scaled by total assets

compromise to reach the final decision. For example, while considering both profitability and naïve extrapolation simultaneously, Stock C might outperform Stock D in profitability, but Stock C might yield worse naïve extrapolation compared to Stock D. In most of the circumstances, investors need to make compromised decisions concerning the complexity and interrelationships of variables/criteria under evaluation.

The idea of the compromised ranking method (VIKOR) aims to select the aspired solution and measure the distances for all alternatives to find out the alternative with the shortest distance to the aspired level. We may assume the alternatives to be expressed as  $A_1, A_2, \dots, A_m$ . The strength of the  $j$ th criterion is expressed by  $f_{kj}$  for alternative  $A_k$ , and  $w_j$  is the influential weight of the  $j$ th variable/criterion, where  $j = 1, 2, \dots, n$ . The compromised alternatives will be chosen while the group utility (average gap) and individual regret be considered according to different settings (basic idea/concept from Yu in 1973) [29]. Individual regret in the VIKOR can be obtained by finding the maximal gap in all criteria for priority improvement. Based on the concepts behind the VIKOR, this research proposes a combined VIKOR-DANP model for glamor stock selection. The steps needed to construct the model will be introduced following the discussion of the ANP.

The ANP method is extended from the AHP (Analytic Hierarchy Process) [30], the AHP is considered suitable to handle complex and multi-criteria decision making. It allows both interactions and feedbacks within cluster of elements (inner dependence) and between clusters (outer dependence). The ANP has been applied widely in social science; for instance, evaluating banking performance [31]. Nevertheless, it is not common to be used for investment evaluation. In the study, the DEMATEL method was applied to adjust the un-weighted supermatrix of the ANP method.

In this research, the proposed model can be divided into two stages. In the first stage, it begins with obtaining the relative influential weights of criteria by the DANP, which used the basic concept of the ANP method by applying the influence matrix of the DEMATEL technique. In the second stage, to assess each alternative stock's performance in the eight criteria, an industrial-benchmarked transformation is processed. Finally, it is transformed into the VIKOR's ranking outputs. The process of the proposed method is shown in Fig. 2, and the details steps may be found in Appendix A.

#### 4. Empirical case for evaluating glamor stocks in semiconductor industry

In this section, an empirical study is presented to illustrate the application of the proposed VIKOR-DANP model to evaluate glamor

stocks from Taiwan's world-leading semiconductor industry as an empirical case.

##### 4.1. Background and problem description

This research aims to develop a MADM approach to select glamor stock for investment. In the previous study [32], researchers have argued that glamor stocks are followed by investors' unrealistic expectation to maintain the stocks' high prices. Glamor stocks often lack of fundamental support in their stock prices. To challenge the difficulty of applying FA for glamor stocks, Mohanram [1] proposed the G-score model, and his study reached a positive outcome. In this research, we extended the original framework of the G-score model to include the evaluation of interrelationships among financial signals for making stock selection decision and improvement strategy.

As Taiwan is a leading country in the semiconductor industry, which plays an important role in promoting technological advancements in the world, the semiconductor sector is one of the hottest industries that keep on attracting global investors' interests. A lot of glamor stocks come from this sector in Taiwan; therefore, we chose it as an empirical case. To examine the effectiveness of the proposed model, the semiconductor industry was chosen to test the glamor stock selection capability in the real financial market.

##### 4.2. Data description

To collect glamor stocks for this study, we used the Taiwan Economic Journal (TEJ) database, sorting the public-listed companies in the Taiwan stock exchange according to their B/M ratios for the end of April 2009. To exclude the industrial influence, we further focused our samples in semiconductor industry. The B/M ratios of those semiconductor stocks ranged from 2.38 to 0.09. This study further defined the top 25% low B/M stocks that belong to the semiconductor industry as glamor stock, and five sample stocks from the glamor stock group were selected as target stocks, namely, MediaTek (A); Sonix Technology (B); Sitronix Technology (C); ITE tech (D); and VIA Technologies (E). Due to the nature of semiconductor industry, companies normally do not have significant advertising expenditure. We replaced the original direct advertising expenditure by Marketing Expenditure ( $C_8$ ) variable in the proposed model. And the diagram of the empirical case can be illustrated as Fig. 3.

According to the G-score model's structure as in Fig. 1, we collected experts' questionnaires as inputs to get the DANP's influential weights. All of the knowledge-based experts (eight experts in

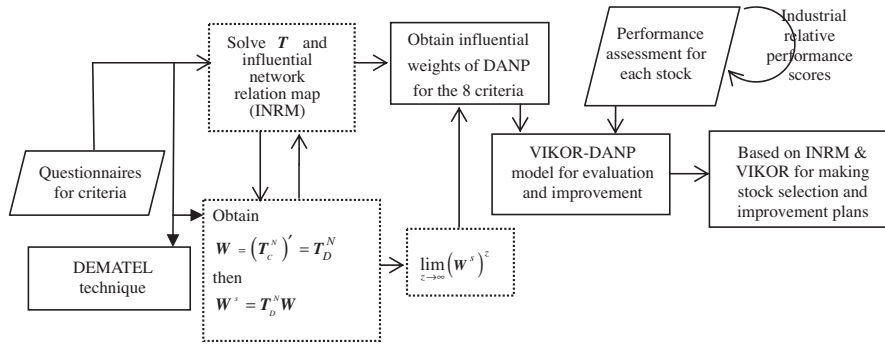


Fig. 2. The processes of proposed method for glamor stock evaluation/improvement.

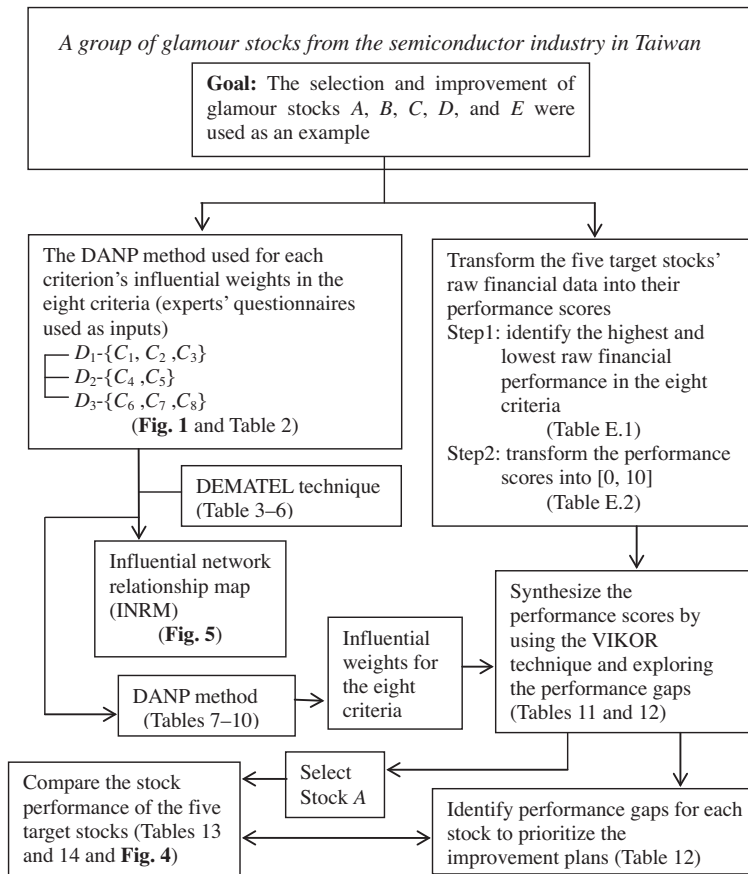


Fig. 3. The diagram of the empirical case.

total) have more than 10 years working experience in investment or finance industry, their job title includes CFO, director, general manager, vice president, analyst, fund manager and manager. To measure the variance of the two variables/criteria of the Naïve Extrapolation ( $D_2$ ) dimension, we calculated the standard deviations of the two variables (i.e.  $C_4$  and  $C_5$ ) by using their four years' records (Table 1) to represent their variances respectively. In financial literature, standard deviation is commonly used to measure investment risk for stocks. As described in Section 3, experts were asked to fill the questionnaire. The questionnaire was used to derive the influential weights of the DANP method for each criterion, and the target stocks' performance scores in each criterion were measured by the stocks' historical performance through a designed transformation.

### 4.3. Measuring influential relationship and influential weights of variables/criteria by using the DANP

The detail steps and Eqs. (A.1)–(A.19) for proceeding the calculations may be found in Appendix A. In brief, we adopted a DEMATEL analysis at first, and the knowledge-based experts (eight domain experts) were asked to give ratings for each criterion for the degree of influence/effect on other criteria. The initial influence matrix  $A$  thus could be obtained by pairwise comparison as Table 2. With significant confidence, the average gap is 3.34%, smaller than 5%; in other words, the significant confidence reaches 96.66%, greater than 95% (see Table 2). Then, the initial average influence matrix  $A$  was normalized by Eqs. (A.2) and (A.3) to get the normalized direct-influence matrix  $D$  (see Table 3 below).



**Table 2**  
The initial influence matrix **A**.

Criteria	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>	C <sub>6</sub>	C <sub>7</sub>	C <sub>8</sub>	Sum
C <sub>1</sub>	–	1.375	2.000	0.500	0.750	0.750	1.875	1.250	8.5000
C <sub>2</sub>	2.750	–	3.000	1.750	3.250	3.125	1.750	3.125	18.750
C <sub>3</sub>	2.000	2.875	–	1.000	3.000	1.125	0.750	2.000	12.750
C <sub>4</sub>	1.000	0.500	3.125	–	2.875	1.125	3.000	.875	12.500
C <sub>5</sub>	3.125	3.375	3.000	2.625	–	2.875	2.000	3.250	20.250
C <sub>6</sub>	2.875	1.250	1.750	1.875	0.625	–	3.000	0.750	12.125
C <sub>7</sub>	1.875	1.750	0.875	0.625	0.750	3.500	–	0.625	10.000
C <sub>8</sub>	1.375	1.000	1.875	1.750	3.250	0.750	0.625	–	10.625
Sum	15.000	12.125	15.625	10.125	14.500	13.250	13.000	11.875	20.250

Note:  $\frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j=1}^n \frac{|a_{ij}^p - a_{ij}^{p-1}|}{a_{ij}^p} \times 100\% = 3.34\% < 5\%$ , where  $a_{ij}^p$  and  $a_{ij}^{p-1}$  denote the average influence of criterion  $i$  on criterion  $j$  by experts  $p$  and  $p - 1$ , respectively;  $n$  denotes the number of criteria. Thus, the results above are confidence of significance at the 96.66% level, which is greater than 95% level that is used to test for significance.

**Table 3**  
The normalized direct-influence matrix **D**.

Criteria	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>	C <sub>6</sub>	C <sub>7</sub>	C <sub>8</sub>	Sum
C <sub>1</sub>	0.000	0.068	0.099	0.025	0.037	0.037	0.093	0.062	0.420
C <sub>2</sub>	0.136	0.000	0.148	0.086	0.161	0.154	0.086	0.154	0.926
C <sub>3</sub>	0.099	0.142	0.000	0.049	0.148	0.056	0.037	0.099	0.630
C <sub>4</sub>	0.049	0.025	0.154	0.000	0.142	0.056	0.148	0.043	0.617
C <sub>5</sub>	0.154	0.167	0.148	0.130	0.000	0.142	0.099	0.161	1.000
C <sub>6</sub>	0.142	0.062	0.086	0.092	0.031	0.000	0.148	0.037	0.599
C <sub>7</sub>	0.093	0.086	0.043	0.031	0.037	0.173	0.000	0.031	0.494
C <sub>8</sub>	0.068	0.049	0.093	0.086	0.161	0.037	0.031	0.000	0.525
Sum	0.741	0.599	0.772	0.500	0.716	0.654	0.642	0.586	

By using Eqs. (A.4) and (A.5), the total-influence matrix for calculating the influential network relationship map (INRM) was obtained as Table 4. After applying Eqs. (A.6)–(A.9), the vector  $r$  and vector  $c$  for finding influential relationship among criteria may be obtained. In addition, the vector  $r + c$  indicates the importance of the  $i$ th criterion, and the vector  $r - c$  in the Eq. (A.9) separates criteria into cause group and effect group. If the element  $r_i - c_i$  is positive, the  $i$ th criterion belongs to the cause group; otherwise, the  $i$ th criterion belongs to the effect group. The result of cause and effect group analysis is shown in Table 5.

To integrate the DEMATEL with the ANP decision method to have the adjusted influential weights, the dimension matrix  $T_D$  (Table 6) and the normalized dimension matrix  $T_D^N$  (Table 7) were calculated as Eqs. (A.13) and (A.14).

The un-weighted supermatrix ( $W = (T_C^N)^t$ ) is the transpose matrix of the normalized direct-influence matrix  $T_C^N$ , which was calculated as Eq. (A.12). The un-weighted supermatrix ( $W$ ) is shown in Table 8. The weighted supermatrix ( $W^s = T_D^N W$ ) thus may be obtained by multiplying  $T_D^N$  by  $W$  (Table 9). The stable limiting supermatrix is arrived by raising power  $z$  of  $\lim_{z \rightarrow \infty} (W^s)^z$ ,

**Table 4**  
The total-influential matrix **T**.

Criteria	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>	C <sub>6</sub>	C <sub>7</sub>	C <sub>8</sub>	$r$
C <sub>1</sub>	0.119	0.165	0.207	0.104	0.149	0.142	0.181	0.154	1.222
C <sub>2</sub>	0.374	0.214	0.387	0.254	0.379	0.354	0.292	0.342	2.595
C <sub>3</sub>	0.280	0.288	0.195	0.179	0.313	0.218	0.193	0.252	1.919
C <sub>4</sub>	0.224	0.181	0.312	0.118	0.289	0.212	0.279	0.184	1.798
C <sub>5</sub>	0.403	0.369	0.405	0.299	0.257	0.357	0.317	0.359	2.766
C <sub>6</sub>	0.281	0.186	0.233	0.184	0.171	0.139	0.268	0.155	1.618
C <sub>7</sub>	0.225	0.190	0.177	0.123	0.154	0.275	0.122	0.136	1.402
C <sub>8</sub>	0.222	0.185	0.250	0.191	0.296	0.174	0.164	0.134	1.616
$c$	2.128	1.778	2.166	1.451	2.008	1.871	1.816	1.716	

**Table 5**  
The analysis of cause and effect on each criterion based on **T**.

Criteria	$r_i$	$c_i$	$r_i + c_i$	$r_i - c_i$
ROA	C <sub>1</sub> 1.222	2.128	3.350	–0.906
Cash flow ROA	C <sub>2</sub> 2.595	1.778	4.374	0.817
CF from operation excess net income	C <sub>3</sub> 1.919	2.166	4.084	–0.247
Less earning variability	C <sub>4</sub> 1.798	1.451	3.249	0.347
Less sales growth variability	C <sub>5</sub> 2.766	2.008	4.773	0.758
R&D expenditure	C <sub>6</sub> 1.618	1.871	3.489	–0.253
Capital expenditure	C <sub>7</sub> 1.402	1.816	3.218	–0.415
Marketing expenditure	C <sub>8</sub> 1.616	1.716	3.332	–0.100

the result (Table 10) shows influential weights of each criterion with regard to evaluating glamor stocks.

4.4. Assessing the target stocks' performance scores based on the VIKOR-DANP model

In the second stage, it begins with how to assess the relative performance of the target stocks in the eight criteria. Instead of

**Table 6**  
The dimension matrix  $T_D$ .

Dimensions		$D_1$	$D_2$	$D_3$	$r_i$	$r_i + c_i$	$r_i - c_i$
Earning & cash flow profitability	$D_1$	0.248	0.230	0.237	0.714	1.494	-0.066
Naïve extrapolation	$D_2$	0.316	0.241	0.285	0.841	1.497	0.184
Accounting conservatism	$D_3$	0.217	0.186	0.174	0.577	1.272	-0.118
	$c_i$	0.780	0.657	0.695			

**Table 7**  
The normalized dimensional matrix  $T_D^N$ .

Dimensions		$D_1$	$D_2$	$D_3$	Sum
Earning & cash flow profitability	$D_1$	0.347	0.322	0.331	1.000
Naïve extrapolation	$D_2$	0.375	0.286	0.339	1.000
Accounting conservatism	$D_3$	0.375	0.323	0.302	1.000

**Table 8**  
The un-weighted supermatrix  $W$ .

Criteria	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$	$C_6$	$C_7$	$C_8$
$C_1$	0.241	0.384	0.367	0.312	0.343	0.401	0.381	0.338
$C_2$	0.336	0.219	0.377	0.253	0.313	0.266	0.321	0.282
$C_3$	0.423	0.397	0.255	0.435	0.344	0.333	0.299	0.380
$C_4$	0.410	0.401	0.364	0.290	0.538	0.518	0.443	0.393
$C_5$	0.590	0.599	0.636	0.710	0.462	0.482	0.557	0.607
$C_6$	0.298	0.358	0.329	0.314	0.346	0.247	0.516	0.368
$C_7$	0.379	0.295	0.291	0.414	0.306	0.477	0.229	0.348
$C_8$	0.323	0.347	0.380	0.272	0.348	0.276	0.254	0.284

**Table 9**  
The weighted supermatrix  $W^F$ .

Criteria	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$	$C_6$	$C_7$	$C_8$
$C_1$	0.084	0.133	0.127	0.117	0.129	0.150	0.143	0.127
$C_2$	0.117	0.076	0.131	0.095	0.118	0.100	0.120	0.106
$C_3$	0.147	0.138	0.089	0.163	0.129	0.125	0.112	0.143
$C_4$	0.132	0.129	0.117	0.083	0.154	0.167	0.143	0.127
$C_5$	0.190	0.193	0.205	0.203	0.132	0.156	0.180	0.196
$C_6$	0.099	0.119	0.109	0.106	0.117	0.074	0.156	0.111
$C_7$	0.126	0.098	0.096	0.140	0.104	0.144	0.069	0.105
$C_8$	0.107	0.115	0.126	0.092	0.118	0.083	0.077	0.086

**Table 10**  
The stable limiting supermatrix while raising power  $z$  of  $\lim_{z \rightarrow \infty} (W^F)^z$ .

Criteria	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$	$C_6$	$C_7$	$C_8$
$C_1$	0.126	0.126	0.126	0.126	0.126	0.126	0.126	0.126
$C_2$	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.109
$C_3$	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131
$C_4$	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132
$C_5$	0.179	0.179	0.179	0.179	0.179	0.179	0.179	0.179
$C_6$	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111
$C_7$	0.110	0.110	0.110	0.110	0.110	0.110	0.110	0.110
$C_8$	0.102	0.102	0.102	0.102	0.102	0.102	0.102	0.102

requesting domain experts to rate the target stocks through questionnaires in the previous VIKOR applications [26,32], this study took a more objective way to obtain the performance scores for the target stocks, that is one of the innovations provided in this study.

Since the stock selection decision has to be made in a specific time point, it is reasonable to compare all of the available stocks' financial data during the decision time window for their relative strength in each criterion. In this study, there were totally 67 stocks that belonged to semiconductor industry by the end of April

2009 in Taiwan. After excluding stocks with incomplete financial data, there were 47 semiconductor stocks left for further analysis. As mentioned earlier, the top 25% low B/M stocks were reckoned as glamor stocks; thus, only 12 ( $47 \times 25\% = 11.75$ ) stocks were regarded as glamor stocks, and we selected five stocks from the 12 stocks for the empirical analysis. However, to make this study closer to practice, all of the 47 stocks' financial performances were considered for the construction of the performance scores for the five sample stocks. The performance scores transformation steps may be described as below:

- Step.1 Find out the best and worst (i.e.  $g_j^*$  and  $g_j^-$  for all criterion,  $j = 1, 2, \dots, 8$ , where  $j$  represents the  $j$ th criterion.) raw financial performance in the eight criteria for the five sample stocks considering all of the 47 semiconductor stocks.
- Step.2 Transform the raw financial performance into range [0, 10] as Eq. (1)

$$p_{kj} = \left( \frac{g_{kj} - g_j^-}{g_j^* - g_j^-} \right) \times 10 \tag{1}$$

where  $p_{kj}$  indicates stock  $k$ 's ( $k = A, B, C, D, E$ ) transformed performance score in the  $j$ th criterion; and  $g_{kj}$  represents the stock  $k$ 's raw financial performance in the  $j$ th criterion for  $j = 1, 2, \dots, 8$ .

- Step.3 Replace  $f_{kj}$  by the five sample stocks' transformed performance score  $p_{kj}$  to conduct the calculation for VIKOR ranking as mentioned in Eqs. (A.16)–(A.19).

Then, by following the step 7, 8 and 9 (see Appendix A), we used the VIKOR method to obtain the ranking indices  $S_k$ ,  $R_k$  and  $Q_k$  of the alternatives (stocks) as in Table 12. The  $r_{kj}$  for each stock in eight criteria was calculated by using Eq. (A.16). Take  $C_1$  in the Table 11 for example, Stock A has the highest performance score 8.826 among the five stocks. To illustrate different considerations of  $Q_k$ , we set  $\nu = 0.7$  to compare the result with  $S_k$  and  $Q_k$  ( $\nu = 1$ ), which provided decision maker another option to consider group utility and individual regret in making comparison.

The ranking results from VIKOR generated consistent ranking for  $S_k$ ,  $Q_k$  ( $\nu = 1$ ) and  $Q_k$  ( $\nu = 0.7$ ). In the calculation for  $Q_k$ ,  $S^-$  and  $R^-$  were both set to be one,  $S^*$  and  $R^*$  were set to be zero while applying Eq. (A.19). The derived outcome is shown in Table 12. The ranking sequence suggests that the Stock A is the top ranking choice by using  $S_k$ ,  $Q_k$  ( $\nu = 1$ ) and  $Q_k$  ( $\nu = 0.7$ ) (see Table 13).

**Table 11**  
The DANP weights and transformed scores for the target stocks.

Criteria	Weights	A	B	C	D	E
$C_1$	0.126	8.826	8.280	7.726	6.435	2.694
$C_2$	0.109	9.515	8.671	5.459	4.788	0.000
$C_3$	0.131	2.835	2.092	0.888	1.286	2.398
$C_4$	0.132	9.033	7.502	6.370	5.336	8.741
$C_5$	0.179	0.967	2.498	3.630	4.668	1.259
$C_6$	0.111	6.611	5.537	6.011	1.282	6.192
$C_7$	0.110	0.729	0.654	2.653	0.360	1.199
$C_8$	0.102	2.028	2.241	2.974	1.799	0.000

Note: The five target stocks are indicated from A to E in this table.

**Table 12**  
Synthesized scores and rankings of target stocks by VIKOR method.

Criteria	Weights	Target stock's gaps to the aspiration levels $r_{kj}^1$				
		A	B	C	D	E
C <sub>1</sub>	0.126	0.117	0.172	0.227	0.357	0.731
C <sub>2</sub>	0.109	0.048	0.133	0.454	0.530	1.000
C <sub>3</sub>	0.131	0.716	0.791	0.911	0.871	0.760
C <sub>4</sub>	0.132	0.097	0.250	0.363	0.978	0.126
C <sub>5</sub>	0.179	0.903	0.750	0.637	0.934	0.874
C <sub>6</sub>	0.111	0.339	0.446	0.399	0.872	0.381
C <sub>7</sub>	0.110	<b>0.927</b>	0.935	0.735	0.771	0.880
C <sub>8</sub>	0.102	0.797	0.776	0.703	0.820	1.000
Total gap		0.510	0.539	0.556	0.778	0.715
Max gap		0.927	0.935	0.911	0.978	1.000
Scores (ranking)						
S <sub>k</sub>		0.510(1)	0.539(2)	0.556(3)	0.779(5)	0.715(4)
R <sub>k</sub>		0.927	0.935	0.911	0.978	1.000
Q <sub>k</sub>	(ν = 1)	0.510(1)	0.539(2)	0.556(3)	0.779(5)	0.715(4)
Q <sub>k</sub>	(ν = 0.7)	0.635(1)	0.658(2)	0.663(3)	0.838(5)	0.800(4)

Note: The total gap of stock A (ranking 1) is 0.510 (when ν = 1), which is better than the other four stocks.

$$^1 r_{kj} = \frac{(f_j^* - f_{kj})}{(f_j^* - f_j^-)}$$

4.5. Examining the stock selection outcome and finding direction for improvement

To examine the effectiveness of the proposed VIKOR-DANP method, this study further explored the relationship between the ranking of target stocks and the corresponding stock's subsequent HPR (holding-period-return) from the end of May 2009 to Dec 2012. In the first glance, the result indicated that stock A outperformed the other four stocks most of the time during the 44 month time period as in Fig. 4. The definition of HPR can be denoted as Eq. (2):

$$HPR = (price_{end} - price_{initial} + dividend_{period}) / price_{initial} \quad (2)$$

In addition, to gain confidence regarding the stock performance differences, we examined the stock performance of monthly average HPRs of the five stocks for two periods (i.e., "from May 2009 to December 2011" and "from May 2009 to December 2012") by using Friedman test and paired t test respectively. The Friedman test was used to examine the ranking result compared with the model's suggested output.

According to Table 12, Stock A was ranked as the top choice, and the ranking sequence should be A > B > C > E > D. But Fig. 4

**Table 13**  
The Friedman test of ranking order in different time periods.

	End of May/2009–December/2011			End of May/2009–December/2012		
	Average HPR	SD of HPR	Mean rank <sup>1</sup>	Average HPR	SD of HPR	Mean rank <sup>1</sup>
Stock A	0.281	0.238	4.41	0.209	0.241	4.36
Stock B	0.209	0.205	3.97	0.144	0.207	4.02
Stock C	0.149	0.189	3.50	0.097	0.185	3.52
Stock D	-0.050	0.215	2.03	-0.175	0.278	2.02
Stock E	-0.395	0.146	1.09	-0.473	0.187	1.07
N (months)		32			44	
Chi-square $\chi^2$		99.050			138.436	
df		4			4	
Sig. <sup>2</sup>		0.000**			0.000**	

<sup>1</sup> The result was generated by the SPSS17 (higher score represents better ranking position; i.e. 4 is better than 3).

<sup>2</sup> The result was significant in 99% confidence level.

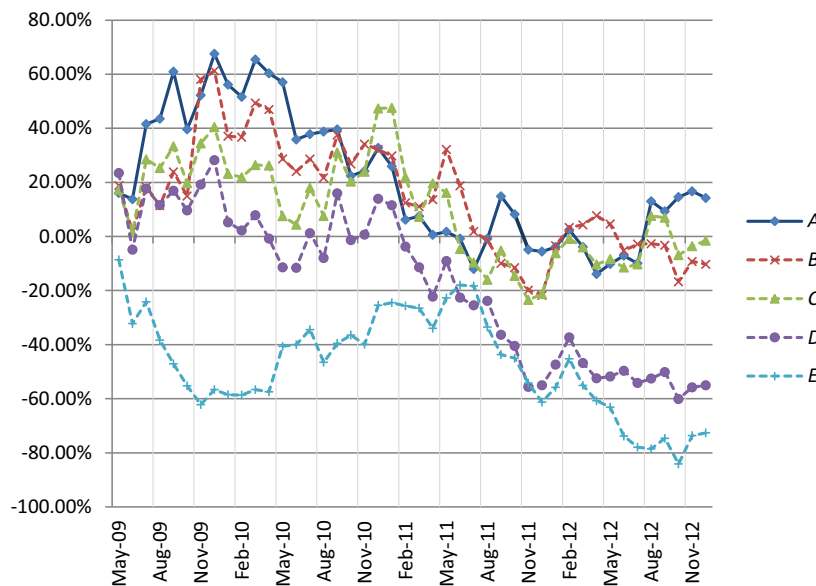


Fig. 4. The HPRs of the five target stocks from May/2009 to December/2012.



**Table 14**  
The paired *t* test of the top three ranking stocks' performance differences.

(End of May/2009–December/2012)	Paired HPR differences				
	Mean	SD	<i>t</i>	df	Sig. <sup>1</sup>
(Stock A–stock B)	0.065	0.161	2.688	43	0.010*
(Stock B–stock C)	0.047	0.119	2.613	43	0.012*

<sup>1</sup> The result was significant in 95% confidence level (2-tailed).

indicates that Stock *D*'s stock performance was better than Stock *E*'s performance during the examined period. However, the top three stocks' performance was in the same ranking order as the model's output; both Stocks *D* and *E* ranked at the bottom of the five target stocks. To further explore the top three target stocks' performance differences, a paired *t* test was conducted for a longer period (from May 2009 to December 2012), as shown in Table 14.

To explore the target stocks' performance gaps in the eight criteria, we calculated the performance gaps to the aspiration levels to find out the priority of improvement strategies. The result is shown in the lower part of Table 12.

4.6. Discussions and implications

The influential analysis among the criteria is shown in Table 4, and the INRM of dimensions and pertinent criteria is illustrated in Fig. 5. In contrast to a general impression, profit-related criteria (i.e.,  $C_1 - C_3$ ) are not the most influential variables. The Less Sales

Growth Stability ( $C_5$ ) and the Less Earning Variability ( $C_4$ ) from the Naïve Extrapolation ( $D_2$ ) dimension gained the first and the second rank in the entire DANP model, as shown in Table 11. The Naïve Extrapolation ( $D_2$ ) dimension has more influence over the other two dimensions ( $D_2 > D_1 > D_3$ ). These findings have implications for the management teams of glamor stocks. To increase the shareholders' value, all management teams seek to increase their stocks' market value by using various strategic plans to make improvements. Because of limited resources, management teams often must prioritize their action plans for improvements or development. The findings of this research suggest that the stability of sales growth and earnings should be kept as first-tier objective in preparing action plans. From the perspective of external investors, the evaluation of glamor stocks should consider the stability of sales and earnings growth as crucial indicators. In other words, the sustainability and persistence should be further examined to ensure the glamor stocks' long-term prospects.

Despite the selection of glamor stocks, this study also helps to identify the performance gaps of the target stocks in each criterion by using the VIKOR method. For example, although the top-ranking Stock *A* performed well in Dimension  $D_2$  (Naïve Extrapolation), its maximal gap (0.927) to the aspiration level was in  $C_7$  (Capital Expenditure), as shown in Table 12. If the firm (Stock *A*) plans to reduce its gap (0.927) to the aspiration level (0), the firm should increase its Capital Expenditure ( $C_7$ ) to catch up with the growth tendency. Besides, Fig. 5 indicates that  $C_8$  (Marketing Expenditure) and  $C_6$  (R&D Expenditure) will influence  $C_7$  (Capital Expenditure). While preparing an improvement plan,

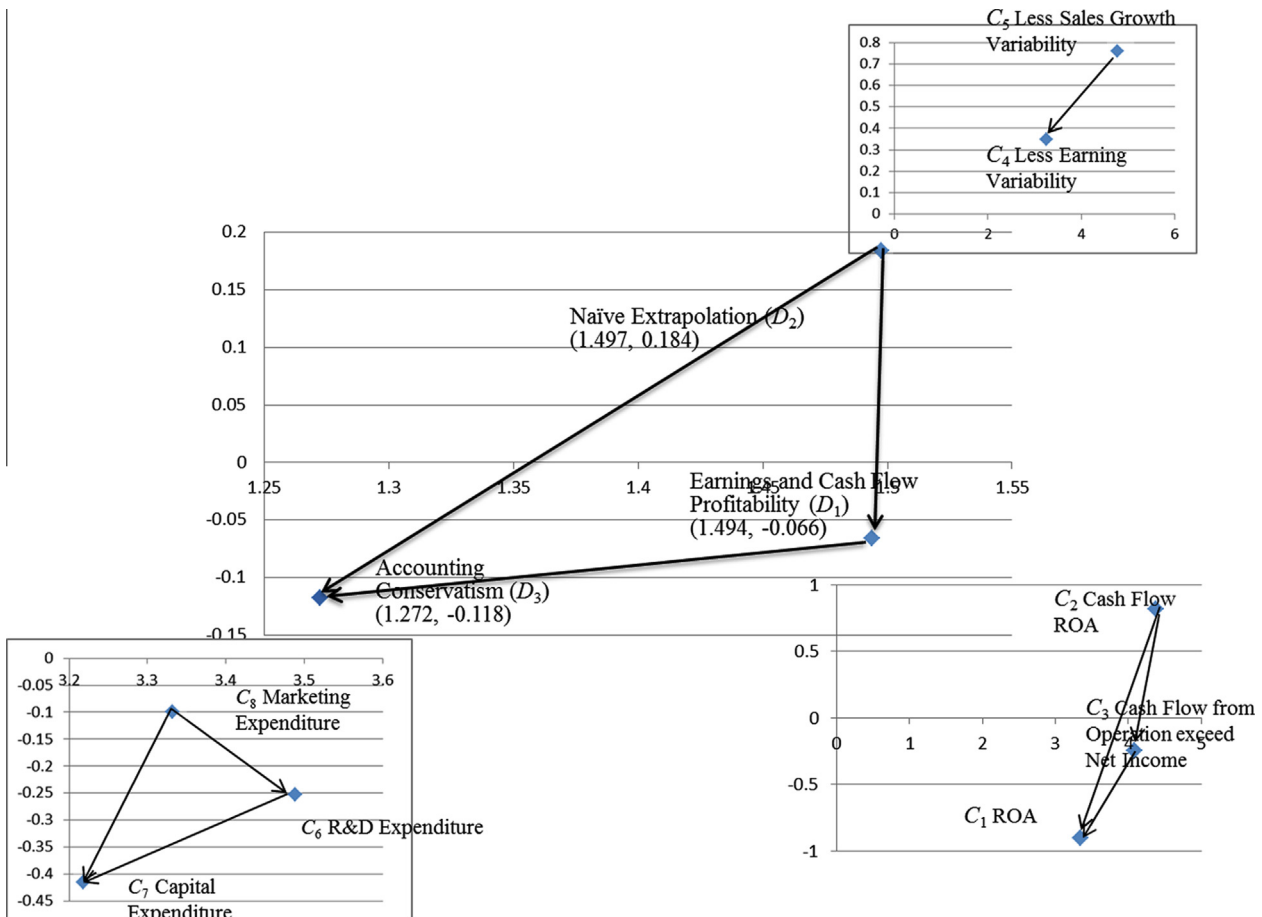


Fig. 5. The INRM of the three dimensions and pertaining criteria.

the increase in marketing and R&D expenditure can both be considered. Furthermore, Fig. 5 also indicates that  $D_3$  is highly influenced by  $D_2$ ; the improvement plans should be examined and conducted carefully to avoid unwanted variability in sales and earnings. Because every stock (company) is constrained by limited resources (mainly financial and human resources), the capability to establish a prioritized improvement plan to gain the highest marginal effect is crucial to a management team. The proposed VIKOR-DANP model demonstrates how to achieve this goal.”

### 5. Conclusions and remarks

In summary, three main outcomes were achieved: (1) The proposed VIKOR-DANP model for glamor stock selection reduced the limitations of the conventional regression models; the independence assumption (among variables) could be removed, and the probability distribution of the dependent variable does not need to be assumed; (2) In the proposed model, Stock A was selected from the five target stocks and outperformed the other four stocks in the subsequent holding period (May 2009 to December 2012), which indicated the effectiveness of the proposed model; (3) In this study, the experts’ knowledge was retrieved to build the influential criteria weights for evaluating the glamor stock (the INRM from the DANP method), and the aspiration level gaps of each stock were measured by the VIKOR method. The obtained INRM and the influential weights provided crucial insights regarding the glamor stock selection and improvement. The measured performance gaps in each criterion may help the management teams of the target stocks to prioritize their improvement plans. This study not only selected the best glamor stock but also found how to improve the gaps to achieve the aspiration level in priority for enhancing future performance. In other words, the proposed model can avoid choosing the best among inferior alternatives [33]. Furthermore, even the best alternative can be guided to achieve the aspiration level through continuous improvement. This is a contribution to the practice of managerial planning.

This study has demonstrated that investment experts’ implicit knowledge can be retrieved by the proposed VIKOR-DANP method while making glamor stock selection. Although the proposed method relies heavily on experts’ judgment, the G-score model provides a theoretical framework to analyze the complex decision processes involved. In addition, to rely less on subjective judgment from the experts, we used a more objective performance transformation approach in this study. The selected top ranking Stock A outperformed the other four stocks under the 44 month HPRs with statistical significance, which indicates that the proposed model is a practical method for glamor stock selection. The proposed model not only takes the interrelations among variables into considerations but also provides relative importance for each criterion regarding growth stock selection.

In addition, the proposed VIKOR-DANP model also integrates experts’ knowledge with industrial relative performance scores for further analysis. The relative performance of each stock within a specific industry is crucial in stock evaluation, which indicates the competitiveness of a stock compared with its peer group. In this study, we proposed a transformation system to obtain the performance scores for target stocks in a more objective way. The obtained improvement priority and INRM provide guidance for management team to refer. Nevertheless, the construction of an in-depth planning for improvement cannot be answered in this study, which may be left for future study.

### Appendix A

#### Stage1: Find total influence matrix for building influential network relation map (INRM) and constructing DANP for obtaining influential weights of each criterion

**Step1:** Obtain the initial average matrix through questionnaire. In the first step, experts are asked to judge the direct effect that they feel factor/criterion  $i$  will have on factor/criterion  $j$ , indicated as  $a_{ij}$ . The scale ranges from 4 (very high influence) to 0 (no influence). To derive the experts’ judgment for further analysis, the initial average matrix takes the arithmetic mean of each respondents’ feedbacks for forming the initial average matrix  $A$ , and the matrix  $A$  is represented as in Eq. (A.1):

$$A = \begin{bmatrix} a_{11} & \cdots & a_{j1} & \cdots & a_{n1} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \quad (A.1)$$

**Step2:** Normalize the initial average matrix for obtaining the direct-influence matrix  $D$ . The matrix  $D = [d_{ij}]_{n \times n}$  can be derived by Eqs. (A.2) and (A.3) as below:

$$D = kA \quad (A.2)$$

$$k = \min \left\{ \frac{1}{\max_i \sum_{j=1}^n a_{ij}}, \frac{1}{\max_j \sum_{i=1}^n a_{ij}} \right\}, \quad i, j \in \{1, 2, \dots, n\} \quad (A.3)$$

**Step3:** Calculate the total-influence matrix  $T$  from the normalized direct-influence matrix  $D$ . By using Eqs. (A.4) and (A.5), the total-influence matrix  $T$  for forming influential network relationship map (INRM) can be obtained. In both Eqs. (A.4) and (A.5),  $I$  denotes the identity matrix.

$$T = D + D^2 + \dots + D^w = D(I - D^w)(I - D)^{-1} \quad (A.4)$$

then,

$$T = D(I - D)^{-1} = [t_{ij}]_{n \times n}, \quad \text{when } w \rightarrow \infty, \quad D^w = [0]_{n \times n} \quad (A.5)$$

**Step4:** Decomposing the total-influence matrix for the analysis of influential effects of criteria. By using Eqs. (A.6) and (A.7), the sum of rows and the sum of columns of the total-influence matrix  $T$  are expressed as vector  $r = (r_1, \dots, r_i, \dots, r_n)'$  and vector  $c = (c_1, \dots, c_j, \dots, c_n)'$  respectively. The superscript denotes transpose operation of matrix. As the vector  $r$  and vector  $c$  have the same number of elements, the operations of  $r + c$  and  $r - c$  will form two column vectors as Eqs. (A.8) and (A.9) for  $i, j \in \{1, 2, \dots, n\}$  and  $i = j$ :

$$r = \left[ \sum_{j=1}^n t_{ij}^j \right]_{n \times 1} = [t_{ij}^i]_{n \times 1} = (r_1, \dots, r_i, \dots, r_n)', \quad j \in \{1, 2, \dots, n\} \quad (A.6)$$

$$c = \left[ \sum_{i=1}^n t_{ij}^i \right]_{1 \times n}' = [t_{ij}^j]_{n \times 1}' = (c_1, \dots, c_j, \dots, c_n)', \quad j \in \{1, 2, \dots, n\} \quad (A.7)$$

$$r + c = (r_1 + c_1, \dots, r_i + c_i, \dots, r_n + c_n)', \quad i \in \{1, 2, \dots, n\} \quad (A.8)$$

$$r - c = (r_1 - c_1, \dots, r_i - c_i, \dots, r_n - c_n)', \quad i \in \{1, 2, \dots, n\} \quad (A.9)$$

In the Eq. (A.8), the  $i$ th element of the column vector  $r + c$  indicates the importance of the  $i$ th criterion. On the other hand, the column vector  $r - c$  in the Eq. (A.9) separates criteria into cause group and effect group. In general, if the element  $r_i - c_i$  is positive, the  $i$ th criterion belongs to the cause group; otherwise, the  $i$ th criterion belongs to the effect group.

**Step5:** Integrating DEMATEL and ANP to develop the un-weighted supermatrix. Based on the total-influence matrix  $T$  obtained from DEMATEL technique, the matrix  $T$  may be normalized to be  $T_C^N$  as Eq. (A.10).

$$T_C^N = \begin{matrix} & \begin{matrix} D_1 & & D_j & & D_n \\ c_{11} \dots c_{1m_1} & \dots & c_{j1} \dots c_{jm_j} & \dots & c_{n1} \dots c_{nm_n} \end{matrix} \\ \begin{matrix} D_1 \\ \vdots \\ D_j \\ \vdots \\ D_n \end{matrix} & \begin{bmatrix} T_c^{N11} & \dots & T_c^{N1j} & \dots & T_c^{N1n} \\ \vdots & & \vdots & & \vdots \\ T_c^{Nj1} & \dots & T_c^{Njj} & \dots & T_c^{Njn} \\ \vdots & & \vdots & & \vdots \\ T_c^{Nn1} & \dots & T_c^{Nnj} & \dots & T_c^{Nnn} \end{bmatrix} \end{matrix} \quad (A.10)$$

To illustrate the normalization process, the element  $T_C^{N11}$  of the  $T_C^N$  can be normalized by Eq. (A.11), and the other elements of  $T_C^N$  follow the same calculation.

$$T_C^{N11} = \begin{bmatrix} t_{C11}^{11}/d_1^{11} & \dots & t_{C1j}^{11}/d_1^{11} & \dots & t_{C1n}^{11}/d_1^{11} \\ \vdots & & \vdots & & \vdots \\ t_{C11}^{11}/d_1^{11} & \dots & t_{C1j}^{11}/d_1^{11} & \dots & t_{C1n}^{11}/d_1^{11} \\ \vdots & & \vdots & & \vdots \\ t_{Cm_11}^{11}/d_{m_1}^{11} & \dots & t_{Cmj}^{11}/d_{m_1}^{11} & \dots & t_{Cm_1n}^{11}/d_{m_1}^{11} \end{bmatrix}$$

In which, the

$$d_i^{11} = \sum_{j=1}^{m_1} t_{Cij}^{11} \quad \text{for } i = 1, 2, \dots, m_1 \quad (A.11)$$

After the normalization of the total-influence matrix  $T$ , the un-weighted supermatrix can be obtained by transposing  $T_C^N$  as in the Eq. (A.12):

$$W = (T_C^N)' = \begin{matrix} & \begin{matrix} D_1 & & D_j & & D_n \\ c_{11} \dots c_{1m_1} & \dots & c_{j1} \dots c_{jm_j} & \dots & c_{n1} \dots c_{nm_n} \end{matrix} \\ \begin{matrix} D_1 \\ \vdots \\ D_j \\ \vdots \\ D_n \end{matrix} & \begin{bmatrix} W^{11} & \dots & W^{1j} & \dots & W^{1n} \\ \vdots & & \vdots & & \vdots \\ W^{j1} & \dots & W^{jj} & \dots & W^{jn} \\ \vdots & & \vdots & & \vdots \\ W^{n1} & \dots & W^{nj} & \dots & W^{nn} \end{bmatrix} \end{matrix} \quad (A.12)$$

In the Eq. (A.12), if a blank or zero appears in the matrix, it indicates that the group or criterion is independent.

**Step6:** Obtain the weighted supermatrix and find out the relative weights of each criterion. To adjust the weights among dimensions, the dimensional matrix  $T_D$  is shown as the Eq. (A.13), which can be normalized to become  $T_D^N$  as in the Eq. (A.14).

$$T_D = \begin{bmatrix} t_D^{11} & \dots & t_D^{1j} & \dots & t_D^{1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{i1} & \dots & t_D^{ij} & \dots & t_D^{in} \\ \vdots & & \vdots & & \vdots \\ t_D^{n1} & \dots & t_D^{nj} & \dots & t_D^{nn} \end{bmatrix} \quad (A.13)$$

$$T_D^N = \begin{bmatrix} t_D^{11}/d_1 & \dots & t_D^{1j}/d_1 & \dots & t_D^{1n}/d_1 \\ \vdots & & \vdots & & \vdots \\ t_D^{i1}/d_i & \dots & t_D^{ij}/d_i & \dots & t_D^{in}/d_i \\ \vdots & & \vdots & & \vdots \\ t_D^{n1}/d_n & \dots & t_D^{nj}/d_n & \dots & t_D^{nn}/d_n \end{bmatrix} = \begin{bmatrix} t_D^{N11} & \dots & t_D^{N1j} & \dots & t_D^{N1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{Ni1} & \dots & t_D^{Nij} & \dots & t_D^{Nin} \\ \vdots & & \vdots & & \vdots \\ t_D^{Nn1} & \dots & t_D^{Nnj} & \dots & t_D^{Nnn} \end{bmatrix} \quad (A.14)$$

The weighted supermatrix can be obtained by multiplying  $T_D^N$  by  $W$  as in the Eq. (A.15), and the limiting supermatrix can be derived from multiplying by itself multiple times until the weights become stable in the matrix.

$$W^S = T_D^N W = \begin{bmatrix} t_D^{N11} \times W^{11} & \dots & t_D^{N1j} \times W^{1j} & \dots & t_D^{N1n} \times W^{1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{Nij} \times W^{ij} & \dots & t_D^{Njj} \times W^{jj} & \dots & t_D^{Njn} \times W^{jn} \\ \vdots & & \vdots & & \vdots \\ t_D^{Nin} \times W^{in} & \dots & t_D^{Nin} \times W^{in} & \dots & t_D^{Nnn} \times W^{nn} \end{bmatrix} \quad (A.15)$$

The influential weights of each criterion can be obtained by  $\lim_{z \rightarrow \infty} (W^S)^z$ . In practice, as long as the limiting supermatrix becomes stable, the process of raising power  $z$  can be stopped to get the final influential weights of each criterion.

**Stage2: Synthesize the ranking scores by combining VIKOR method**

In the second stage, the compromise ranking method (VIKOR) is applied to select the target alternatives (stocks) for minimizing the synthesized gap to the aspired level. Opricovic and Tzeng [34] proposed VIKOR for the ranking problem in MADM field. The VIKOR method based modification for adjusting DANP matrix can be described as below [35]. Assuming that the alternatives are expressed as  $A_1, A_2, \dots, A_m$ . The performance of the  $j$ th criterion is denoted by  $f_{kj}$  for alternative  $k$ ,  $w_j$  is the weight of the  $j$ th criterion, where  $j = 1, 2, \dots, n$ , and  $n$  is the number of the criteria. The VIKOR begins with  $L_p$ -metric, in which the  $L_k^p = \left\{ \sum_{j=1}^n [w_j (|f_j^* - f_{kj}|) / (f_j^* - f_j^-)]^p \right\}^{1/p}$ , the compromised alternative based on  $\min_k L_k^p$  would be chosen because its value is closest to the ideal level.

**Step7:** Normalize the original rating matrix. At first, choose the best  $f_j^*$  and the worst  $f_j^-$  for all criteria,  $j = 1, 2, \dots, n$ , where  $j$  represents the  $j$ th criterion. While the  $j$ th criteria represents a benefit, and the best implies  $f_j^* = \max f_{kj}$  and  $f_j^- = \min f_{kj}$  respectively. An original rating matrix can be transformed into a normalized matrix by

$$r_{kj} = \left( \frac{f_j^* - f_{kj}}{f_j^* - f_j^-} \right) \quad (A.16)$$

**Step8:** Compute the rating indexes. To obtain  $S_k$  and  $R_k$  by

$$S_k = \sum_{j=1}^n w_j r_{kj} \quad (A.17)$$

and

$$R_k = \max_j \{r_{kj} | j = 1, 2, \dots, n\} \quad (A.18)$$

where  $S_k$  and  $R_k$  represent the mean of group utility (shown as “average gap”) and maximal regret (shown as “maximal gap”) in all criteria) respectively.

**Step9:** Compute the index values  $Q_k$ ,  $k = 1, 2, \dots, m$ .

$$Q_k = v \frac{(S_k - S^*)}{(S^- - S^*)} + (1 - v) \frac{(R_k - R^*)}{(R^- - R^*)} \quad (A.19)$$

where  $S^* = \min S_k$  (or set  $S^* = 0$ ),  $S^- = \max S_k$  (or set  $S^- = 1$ ) and  $R^* = \min R_k$  (or set  $R^* = 0$ ),  $R^- = \max R_k$  (or set  $R^- = 1$ ). Eq. (A.19) can be rewritten as:  $Q_k = vS_k + (1 - v)R_k$ . In which,  $v$  is introduced as a weight for the strategy of maximal group utility,  $(1 - v)$  is the weight of the individual regret (shown as “maximal gap”) in all criteria).

**Step10:** Rank the alternatives. By sorting the values  $S_k$ ,  $R_k$  and  $Q_k$ , for  $k = 1, 2, \dots, m$ , to get the final result. Moreover, we transfer this ranking concept into finding priority of improvement and sorting the gaps for reducing gaps in each criterion based on the INRM.

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