Strategic Financial Performance Evaluation of the Iranian Automotive Industry Using Imperialist Competitive Algorithm

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ABSTRACT

Objective. This paper evaluates strategic financial performance of 10 Iranian stock exchange listed automotive companies over the period 2005–2009 at the hand of value-creating performance indicators and the Free Cash Flow derived value indicators.

Methodology. To this effect, profiting from the Imperialist Competitive Algorithm (ICA), the understudy companies were assigned to three clusters in terms of debt structure, firm size, and growth opportunities.

Findings. The results, in general, indicate a significant correlation between value-based indicators Economic Value Added (EVA) and True Value Added (TVA) and the FCF-derived indicators Created Value from Free Cash Flow to Firm (CVFCFF) and Created Value from Free Cash Flow to Equity (CVFCFE), and between Market Value Added (MVA) and CVFCFF (one of the two FCF-derived indicators), while, according to the results, there is no significant correlation between the value-driven performance indicators Refined Economic Value Added (REVA) and Equity Economic Value Added (EEVA) and either of the FCF-derived indicators CVFCFF and CVFCFE.

Originality/Value. In present study, the companies are clustered by ICA based on their close similarity in all three criteria (debt structure, firm size, and growth opportunities). Subsequently, for investigating the relationship between each of the strategic performance indicators correlation and Fisher (F) test are used.

KEYWORDS: Performance Evaluation, Value creation, Algorithm, Automotive Industry.

1 INTRODUCTION

The performance of business activities relates to the rate of utilization of the competitive advantages of every firm. It is very difficult for a firm, particularly in the age of fast development of business environment, to support these competitive advantages. Just the companies, which respond to the changing business situations and which monitor and ceaselessly evaluate the level of
performance and put attempts to continuously increase it, may further develop with success (Pavelková & Dostál, 2013).

Value creation, a process in which people and organizations are engaged for different reasons in pursuit of their own gains, plays a crucial role in management of modern organizations. Among the group of stakeholders, shareholders take a special position, for the crucial role they assume as entrepreneurs and founders of the enterprise, and for the relatively higher risk they take. The shareholder created value is realized once the enterprise has paid out the other stakeholders their share from the total created value, and the art of management is to incorporate all interested parties into a balanced system of value distribution. In doing so, equity shareholders would eventually come to their own share of the created value and would become encouraged to keep on investing in the firm.

Investors and financial managers nowadays expect using reliable indicators to get access to the information which reflects real profit, cash status, earnings potential, and growth opportunities of the firm and enables analysis of the risk involved. Hence, the choice and use of an appropriate indicator for evaluation of and surveillance over company performance has become increasingly important, since it helps achieving the aimed company objectives by allowing timely detection of any possible deviation from desired level of performance and making adjustments thereof. Thus far, for evaluation of company performance, many firms have been traditionally making use of certain key accounting indicators such as sales (growth), profit and percentage of profit to sales. Despite the wide use of these indicators in practice, they fail to properly assess managerial performance, since earnings of business unit is closely related to investment rate, and none of the traditional indicators take account of investment price (Kaviani, 2013). Hence, a historical viewpoint on the evaluation of performance reveals the evolution of thinking about this measuring and of the concepts of performance from the measuring of profit margins and the growth of profit for measurement of return on capital (ROC) to modern concepts based on the creation of value for the shareholders and the value based management. There is nowadays a world-wide debate between specialist represented by consultancy firms, the universities and managers of companies on the choice of the best management and measuring of performance concept. The economics experts describe it often as a war of indicators between traditional indicators (ROI, ROE, ROA, EPS, P/E,….) and modern indicators based on the value based management (MVA, EVA, REVA, CFROI, Shareholder Value,….) (Bonaci, Matis, & Strouhal, 2010).

As a solution to the issue of possible manipulation or distortion of the traditional, accounting-based profit/performance indicators, many analysts have appealed to cash flow based indicators as more concrete and less manipulable alternatives. And the subsequently introduced Free Cash Flow (FCF) concept laid the foundation for development of a variety of performance measurement models and approaches among which Free Cash Flow to Firm (FCFF) and Free Cash Flow to Equity (FCFE) were the most important ones.
The two models were later on further linked to value creation by Kaviani (2013), resulting in Created Value from Free Cash Flow to Firm (CVFCFF) and Created Value from Free Cash Flow to Equity (CVFCFE).

To sustain their compensation level and further boost it, managers, taking advantage of the accounting flaws, gradually engaged in practice of earnings management. And that was the reason why some companies despite an apparently satisfactory financial position were actually struggling with acute liquidity shortage (or drying up of liquidity). These facts, among others, implied inadequacy of the applied accounting performance indicators and the associated managerial bonus plans in serving collective interests of the organizational stakeholders, especially those of the equity shareholders, and mitigating the conflict of interests. Hence, the new indicators which came as remedy to shortcomings of the traditional (accounting ones) were increasingly focused on the real economic flow of the business operation. Since appearance of the economic profit or Residual Income theory, a number of models have been proposed for its calculation. Economic profit is viewed as a source of value creation for businesses by boosting their stock prices on the market.

An economic profit making enterprise would suggest a value creating enterprise, and a business viewed as such would experience a proportional rise in its share market price, producing more wealth for its shareholders (Largani & Kaviani, 2014). In this regard, a wide range of value-creating performance indicators have been introduced, including EVA, MVA, REVA, Adjusted Economic Value Added (AEVA), Shareholder Value Added (SVA), Created Shareholder Value (CSV), Cash Flow Return on Investment (CFROI), and Cash Value Added (CVA). But, as regards the Iranian capital market, two of the value-driven indicators, namely EEVA, a construct proposed by (Damodaran, 2012), and TVA, the concept introduced by Mohanty (2004), have not been yet investigated for the companies operating on this market.

Due to the difficulty and intricacy involved in calculation of value-driven indicators, numerous studies, took preferably a roundabout course by having themselves occupied with the relationship assumed to be existing between the value-driven indicators and accounting profit (performance) indicators for estimate of the former indicators from information content conveyed by the latter ones. From among the value-driven indicators, EVA, MVA, and REVA have been most frequently used and indicators AEVA, SVA, CVACFROI, CSV, EEVA and TVA have been to a less degree applied for this purpose.

In addition, few studies have been so far conducted on the relationship of value-creating performance indicators with cash flow based indicators the most important of which outside the country were the works of O’Byrne (1996), Shrievess & Wachowicz Jr (2001), and Worthington & West (2004), while recently Kaviani (2013) and Kaviani, Batebi, & Shahmanosuri (2014) have addressed the issue in two separate works by examining the relationship of EVA, EEVA, and TVA with CVFCFF and CVFCFE through multiple regression.

The results of the last two studies indicated significant correlation of EVA and TVA with CVFCFF and CVFCFE, and no significant correlation between
EEVA and CVFCFF and CVFCFE. In these studies, the correlation between the mentioned performance indicators concerned the whole sample and the understudy companies despite being from the same industry were not classified in terms of debt structure, firm size, and growth opportunities. In present work, however, this issue is dealt with using ICA whereby the companies primarily are brought under three homogeneous clusters. The obtained results from test of each cluster and the overall results for the aggregate data appear to be closer to reality relative to the results obtained in the earlier works.

This study, in line with and in elaboration on two previously conducted researches by Kaviani (2013) and Kaviani et al. (2014), profiting from ICA approach investigates relationship of the value-based performance indicators EVA, EEVA, TVA, MVA, REVA (the last two ones are added in present study) with CVFCFF and CVFCFE through correlation analysis and a bivariate regression model. The advantages of the use of Meta-heuristic algorithms in finance and economy were described by different authors (Bermúdez, Segura, & Vercher, 2012; Chen, Ribeiro, Vieira, Duarte, & Neves, 2011; Etemadi, Rostamy, & Dehkordi, 2009; Gordini, 2014; Huang, 2012; Kim & Han, 2003; Kim & Kang, 2012; Min, Lee, & Han, 2006; Shin & Lee, 2002; Varetto, 1998; Wu, Tzeng, Goo, & Fang, 2007). The logic underlying ICA suggests initial clustering of the sample companies by debt structure, firm size, and growth opportunity and subsequent statistical test and analysis of each individual cluster in isolation.

It should be noted that clustering in this approach aims to make distinction between companies by debt structure, growth opportunity, and size which in prior research used to be applied to assessment of the relationship between independent and dependent variables as control factors in multiple regression models. However, in present research, by company clustering in ICA environment, the companies are clustered based on their close similarity in all three criteria and subsequently for examination of each strategic performance indicator were subjected to correlation and Fisher (F) tests. Debt structure measured by leverage (Total debt to Total Assets), Firm size defined as Natural logarithm of Total assets and Growth opportunities as measured by Tobin’s q (Tobin’s q is calculated by dividing the market value of a firm by the replacement value of the book equity). Hence, in this paper, Debt structure, Firm size and Growth opportunities are as Inputs for clustering of firm.

It is noteworthy that ICA here does not examine any relationship, but deals with clustering of the companies with close characteristics to each other, so as statistical analysis for each cluster is expected to significantly help accuracy of the obtained results from test of the hypotheses (i.e. confirmation or rejection of hypotheses) for companies of varying size, debt structure, and growth opportunity. The use of these variables (in such analyses) is primarily justified by their theoretically assumed or formulated effects on value-creating performance indicators (e.g. the effect of debt structure via cost of equity capital). On the other hand, the division of companies into three main clusters formed based on their debt structure, size, and growth opportunity has led to application of these features as control variables by a large number of financial studies.
Given the influence of control variables in relationship of independent and dependent variables and in verification of hypotheses, and since by application of ICA approach the influence of these variables is already taken account of by dividing the companies into homogeneous clusters in terms of size, debt structure, and growth opportunity, no control variable will be included in the regression model (i.e. a bivariate regression is used in place of a multivariate regression), so as the test of hypotheses for each cluster is performed by a bivariate regression or simply by correlation analysis and in terms of correlation coefficient. As a result, in each cluster of companies the hypothesis for which a greater weight (coefficient) in terms of either confirmation or rejection is obtained will serve as the criterion to arrive at final decision on confirmation or rejection of the assumed relationship.

2 RESEARCH METHOD

2.1 Sample and data
Given the thinness of the Iran capital market, this study uses all publicly traded firms on Tehran stock exchange (TSE) during the period of 2005–2009. Data base on records of financial statements and market data of all Iranian firms that are listed on Automotive Industry, and that are subject to the regulations by the Capital Market Authority in Iran. Listed firms were then screened against several factors; and remaining firms were then tested for availability of financial data during the test period (2005–2009). This screening yielded a final sample of 10 firms.

2.2 Variables measurement
Dependent variables
This study uses Imperialist competitive Algorithm for Performance Evaluation of the Iranian firms. A company creates value for the shareholders when the shareholder return exceeds the share cost. In other words, company creates value in one year when it outperforms expectations. CVFCFF is computed as

\[ \text{EMV}_t \times \left( \frac{\text{FCFF}_{t+1}}{\text{EMV}_t} - \text{WACC} \right) \]

that, FCFF\(_ {t+1} \) computed as

\[
\text{Net Income} + \text{Noncash Charge} + [\text{Interest Expense} \times (1 - \text{tax rate})] \\
- \text{Fixed Capital Investment} - \text{Working Capital Investment}. 
\]

Also, CVFCFE is computed as

\[ \text{EMV}_t \times \left( \frac{\text{FCFE}_{t+1}}{\text{EMV}_t} - r \right) \]

that,

\[ \text{FCFF} - [\text{Interest expense} \times (1 - \text{tax rate})] + \text{net borrowing} \]
and \( r \) is Required Return to Equity.\(^1\)

**Independent variable (Value creation)**

Independent variables are measures of value creation (EVA, REVA, MAV, TVA, and EEVA). EVA is the amount of economic value added for the owners by management. The thrust area for today's management is to find means to create value for the owners. Under EVA, all distortions in conventional accounting are identified and accounting profit is adjusted to make it distortion free and finally we get the amount of EVA. Stewart (1990) defined EVA as Net Operating profit after taxes (NOPAT) subtracted with a capital charge. Algebraically, it can be stated as follows:

\[
EVA = NOPAT - WACC(CAPITAL). \tag{1}
\]

In (1), NOPAT is the net operating profit after taxes; WACC is the cost of capital; and CAPITAL is total capital. REVA is an extension to the EVA methodology, providing an analytical framework for evaluating corporate performance in the context of shareholder value creation. The current methodology uses market values for the firm's assets along with a market-derived cost of capital. The rationale of the REVA is that since in the calculation of EVA the capital charge for the firm is derived from a market-based weighted average cost of capital then it is not appropriate to use the economic book value of assets (Kaviani, Biabani, & Azam, 2012):

\[
REVA = NOPAT - WACC(MCAPITAL),
\]

where, MCAPITAL is the Total Market Value of the firm's assets at the end of period.

MVA measure is based on the assumption that the total market value of a firm is the sum of the market value of its equity and the market value of its debt. MVA is the difference between the current market value of a firm and the capital contributed by its investors (Kaviani et al., 2012):

\[
MVA = \text{current market value of a firm} - \text{capital contributed by its investors.}
\]

If the MVA is positive, the company has created wealth for its shareholders. If it is negative, then the firm has destroyed value. And finally EEVA is calculated using this formula:

\[
\left( \text{Return on equity} - \text{Cost of equity} \right) \times \left( \text{Equity invested} \right),
\]

and TVA is calculated as follows:

\[
\text{Free Cash Flow} - \text{Capital Gains} - \left( \text{Market Value} \times (1 + WACC) \right).
\]

\(^1\)Net borrowing = (long- and short-term new debt issues) − (long- and short-term debt repayments).
3 IMPERIALIST COMPETITIVE ALGORITHM FOR CLUSTERING

The meta-heuristic algorithms is one of the most common techniques used for clustering (Senthilnath, Omkar, & Mani, 2011; Yazdani & Jolai, 2015). Clustering techniques have received considerable attention in wide range of study such as medicine, engineering, data mining and biology (Niknam, Taherian Fard, Pourjafarian, & Rousta, 2011).

On the other hand, the meta-heuristic algorithms have been applied successfully to problems in Economics and Finance in the last decades (Abdou, 2009; Ahn & Kim, 2009; Varetto, 1998). This paper presents an evolutionary optimization algorithm which is called imperialist competitive algorithm, for optimum clustering $N$ companies into $K$ clusters. With this motivation, in this section we use an ICA for clustering. ICA is a new population based meta-heuristic which introduced by Atashpaz-Gargari & Lucas (2007) for solving continuous optimization problems and in recent years many researcher modify it to overcome the wide range of problems problem (Afonso, Mariani, & Coelho, 2013; Anjomshoa, Mahani, & Sadeghifard, 2014; Azadeh, Seif, Sheikhalishahi, & Yazdani, 2015; Duan, Xu, Liu, & Shao, 2010; Kaveh & Talatahari, 2010; Mahari & Zare, 2014; Moghaddam, 2013; Moradi & Zandieh, 2013; Razmjoo, Mousavi, & Soleymani, 2013; Shamshirband et al., 2014; Yazdani, Fariborz, Khalili, & Shiripour, 2014; Yazdani & Jolai, 2013).

Atashpaz-Gargari & Lucas (2007) proposed and described the algorithm as

Like other evolutionary ones, this algorithm starts with an initial population. In this algorithm any individual of the population is called a country. Some of the best countries (in optimization terminology, countries with the least cost) are selected to be the imperialist states and the rest form are the colonies of these imperialists. All the remained colonies of initial countries are divided among the mentioned imperialists based on their power. The power of each country is calculated from the objective function of the proposed model.

After dividing all colonies among imperialists and creating the initial empires, these colonies start moving toward their relevant imperialist country. This movement is a simple model of assimilation policy which was pursued by some of the imperialist states. The total power of an empire depends on both the power of the imperialist country and the power of its colonies. For this fact, we consider the total power of an empire as the sum of power of imperialist country and a percentage of mean power of its colonies.

Then, the imperialistic competition begins among all the empires. Any empire that is not able to succeed in this competition and increase its power (or at least prevent decreasing its power) will be eliminated from the competition. The imperialistic competition will gradually result in an increase in the power of powerful empires and a decrease in the power of weaker ones. Weak empires will lose
their power and ultimately they will collapse. The movement of colonies toward their relevant imperialists along with competition among empires and also the collapse mechanism will hopefully cause all the countries to converge to a state in which there exist just one empire in the world and all the other countries are colonies of that empire. In this ideal new world, colonies have the same position and power as the imperialist.

3.1 Initialization: Solution Representation and Population Generation
The first step in the ICA, like other evolutionary algorithms, is to create the initial solutions. Every solution in ICA is called a country which corresponds to a chromosome in Genetic Algorithm. In an \( N \)-dimensional optimization problem, a country is shown by a \( 1 \times N \) array. This array is defined as

\[
Country = [p_1, p_2, \ldots, p_N].
\]  

Cost (fitness value) of each country is computed by evaluating the cost function, as

\[
Cost = f(Country) = f(p_1, p_2, \ldots, p_N).
\]  

The algorithm starts with \( N_{pop} \) initial countries and \( N_{imp} \) of most powerful countries chosen as imperialists. The remaining countries \( (N_{col} = N_{pop} - N_{imp}) \) will be the colonies of powerful countries. Initiated countries fall into two kinds of countries; colony and imperialist. Colonies are assigned to emperors according to proportional power of each emperor, \( P \), which is obtained by computing the normalized cost for each emperor as

\[
P_k = \left\lfloor \frac{C_k}{\sum_{i=1}^{N_{imp}} C_i} \right\rfloor.
\]  

The normalized power of each imperialist reveals the approximate number of colonies that should be possessed by that imperialist. Then, the number of colonies which belong to the \( K \)-th Empire will be about

\[
NC_k = \text{Round}(P_k N_{col}),
\]  

where \( NC_k \) is the number of colonies of \( k \)-th empire and \( N_{col} \) is the total number of colonies assigned to this empire. Figure 1 presents the preliminary empires.

3.2 Assimilation: Moving the Colonies of An empire Toward the Imperialist
In assimilation policy, the colonies start moving toward their imperialist country. This movement is shown in Figure 2. As shown in Figure 2, the colony moves toward the imperialist by \( x \) units where \( x \) is a Uniform random variable as follows:

\[
x \sim U\left(0, \beta \times d\right), \quad \beta > 1,
\]
where $d$ is distance between the colony and its imperialist and $\beta$ is a constant value. The assumption $\beta > 1$ causes the colonies to get closer to the imperialist from both sides.

To search a wider area around current imperialist, a random value with Uniform distribution is added to the direction of movement:

$$\theta \sim U(-\gamma, \gamma),$$

where $\gamma$ is a number that adjusts the amount of deviation from the original path.

### 3.3 Exchanging Positions of the Imperialist and the Colony

While moving toward the imperialist, a colony may reach to a better position. In such a case, imperialist will exchange their positions by colony. Then, the algorithm will be continuing by the new imperialist country.

### 3.4 Computing Total Cost of an Empire

Total power of each empire is determined by the power of an imperialist and its colonies. So, we model total cost of $k$-th empire as follows:

$$TC_k = Cost(\text{Imperialist}_k) + \xi \cdot \text{Mean}(Cost(\text{Colonies of Empire } k)),$$

where $TC_k$ is the total cost of $k$-th Empire and $\xi$ is a positive value between 0 and 1. It is obvious that smaller amount for $\xi$ causes the cost of $n$-th imperialism to be close to the cost of $k$-th emperor.
3.5 Imperialistic Competition
In imperialistic competition algorithm, each empire tries to take the possession of the colonies of the other empires and control them. This struggle gradually brings about a decrease in the power of weaker empires and eliminating weaker ones. Success in this imperialistic competition is depending on the power of each empire. Stronger imperialist has more chance to take possession of weakest countries in weakest empires. Possession probability of each empire, computed based on total power of that empire. Normalized total cost of \( k \)-th empire is computed as

\[
NTC_k = TC_k - \max_i \{TC_i\}, \quad i = 1, 2, \ldots, N_{imp},
\]

where \( NTC_k \) and \( TC_k \) are respectively normalized total cost and total cost of \( k \)-th Empire.

Now, the possession probability of each empire is given by

\[
p_k = \frac{NTC_k}{\sum_{i=1}^{N_{imp}} NTC_i}.
\]

To distribute colonies among empires based on their possession probabilities we form vector \( P \) as

\[
P = [p_1, p_2, p_3, \ldots, p_{imp}].
\]

Then, we create a vector \( R \) with the same size as \( P \) whose elements must be uniformly distributed random values between 0 and 1,

\[
R = [t_1, t_2, t_3, \ldots, t_{imp}], \quad t_1, t_2, t_3, \ldots, t_{imp} \sim U(0, 1).
\]

We obtain vector \( D \) as

\[
D = P - R = [D_1, D_2, \ldots, D_{imp}] = [p_1 - r_1, p_2 - r_2, \ldots, p_{imp} - r_{imp}].
\]

Referring to vector \( D \), we will give the mentioned colonies to an empire whose \( D \)-index is the highest.

3.6 Eliminating the Powerless Empires
In imperialistic competition, weaker empires will collapse and their colonies will be assigned to others. In this research it is assumed that an empire collapses when it cannot develop its colonies and loses all of them.

3.7 Convergence
After a while, all empires, except the most powerful one, lose their power and their colonies and will be under the control of this most powerful empire. In this condition, we put an end to the imperialistic competition and the algorithm stops.
Table 1: Parameters of the ICA

| Parameters                | Value |
|---------------------------|-------|
| Number of initial countries | 200   |
| Number of initial imperialists | 10    |
| Number of iterations      | 500   |
| Revolution rate           | 0.1   |
| $\beta$                   | 2     |
| $\xi$                     | 0.1   |

3.8 Clustering

The algorithm is implemented by using MATLAB and the parameters of the ICA are presented in Table 1.

As is shown in Figure 3, after grouping companies with similar characteristics (these character are: Debt structure, size and Growth opportunities) into three group; first group consist of 4 companies and second and third group each have 3 companies. For every group correlation test and F test were studied which result of these study will be explained in next sections.

Figure 3: Centers and clustered data

4 Data analysis

4.1 Descriptive statistics

To get a better insight into the nature of the population under study and become more acquainted with the research variables, before analysis of the statistical data, a preliminary general description of their features and characteristics is often required. Besides, data statistical description is a necessary step towards identification of their overall pattern which lays the foundation for further exploration of the existing relationships between research variables. The research descriptive statistics are summarized in Table 2.
Table 2: Results of the descriptive statistics (in millions of Iranian Rials)

| Variables | Minimum | Maximum | Mean     | Standard deviation |
|-----------|---------|---------|----------|-------------------|
| Independent CVFCFF | −0.88574 | 17.96026 | 1.234119 | 3.645282           |
| CVFCFE    | −0.78134 | 14.65597 | 1.054718 | 2.996371           |
| Dependent EVA     | −209,241 | 5,689,100 | 634,792.4 | 1,456,129          |
| MVA       | −0.77792 | 15,204   | 1.546337 | 3.790297           |
| REVA      | −5,404,070 | 184,521  | −307,553 | 889,400.1          |
| TVA       | −32.6467 | 0.066788 | −3.95872 | 7.086523           |
| EEVA      | −3.49769 | 0.100173 | −0.09866 | 0.503446           |

Table 2 presents descriptive statistics of the used value-creation indicators in the present research. As is seen, there is a difference in terms of sign (positivity or negativity) among the industry mean values, i.e. the industry mean values for some of the indicators (EEVA, TVA, REVA) are negative, while for some other are positive. This indicates varying information content attached to each value-added indicator from a different perspective.

4.2 Test hypotheses

Table 3 indicates the results of the analysis for 4 companies in cluster 1. According to the results presented in Table 3, there is a significant correlation between the value-driven indicators EVA and TVA and the FCF-derived indicators (CVFCFF, CVFCFE). The correlation coefficients are presented in Table 3 alongside other statistical measures such as R², F-statistic, and linearity tests.

Table 3: The results of data analysis for cluster 1

|          | EVA   | MVA   | REVA  | TVA   | EEVA  |
|----------|-------|-------|-------|-------|-------|
| CVFCFF   |       |       |       |       |       |
| Pearson  |       |       |       |       |       |
| Correlation |       |       |       |       |       |
| $R^2$    | 0.705 | 0.223 | −0.129 | −0.491 | −0.526 |
| (Adj. $R^2$) | (0.469) | (−0.003) | (−0.038) | (0.198) | (0.236) |
| F        | 17.786 | 0.943 | 0.307 | 5.705 | 6.885 |
| N        | 20     | 20    | 20    | 20    | 20    |
| Linearity | Yes   | No    | No    | Yes   | Yes   |

|          |       |       |       |       |
|----------|-------|-------|-------|-------|
| CVFCFE   |       |       |       |       |       |
| Pearson  |       |       |       |       |       |
| Correlation |       |       |       |       |       |
| $R^2$    | 0.738 | 0.857 | −0.063 | −0.883 | −0.152 |
| (Adj. $R^2$) | (0.520) | (0.720) | (−0.051) | (0.768) | (−0.031) |
| F        | 21.554 | 49.842 | 0.072 | 63.833 | 0.426 |
| N        | 20     | 20    | 20    | 20    | 20    |
| Linearity | Yes   | Yes   | No    | Yes   | No    |

*** $p$-value < 0.01; ** $p$-value < 0.05; * $p$-value < 0.1.
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The indicated correlation coefficients \( R^2 \) in the table suggest 49.7 and 24.1 percent of changes in CVFCFF are explained by EVA and TVA indicators, respectively, while 54.5, 73.5, and 78 percent of changes in CVFCFE are explained by EVA, MVA, and TVA, respectively. However, the results in Table 3 do not support a significant relationship between REVA and EEVA (value-based indicators) and CVFCFF and CVFCFE (FCF-derived indicators).

The results of the analysis for 3 companies in cluster 2 indicate significant correlation of EVA, MVA and TVA with CVFCFF and CVFCFE (at Sig. below 0.05). In this relationship, EVA and MVA are directly, and TVA inversely correlated to the corresponding variables, where the correlation of EVA both with CVFCFF and CVFCFE was the most strong and significant one. The indicated correlation coefficients \( R^2 \) in Table 4 suggest 80.3, 52.6, and 47 percent of changes in CVFCFF, and 80, 45.9, and 39.5 percent of changes in CVFCFE are explained by EVA, MVA, and TVA, respectively. However, the results of Table 4 do not confirm any significant relationship between REVA and EEVA (as value indicators) and CVFCFF and CVFCFE (as FCF-derived indicators). And finally, Table 5 provides the results on analysis for 3 companies brought under cluster 3.

According to the results of Table 5, there is no significant correlation between the value-creating performance indicators and the FCF-derived indicators, implying different results from test of the hypotheses for the homogeneous clusters of companies. As a consequence, the results derived from test of the

Table 4: The results of data analysis for cluster 2

|        | EVA | MVA | REVA | TVA | EEVA |
|--------|-----|-----|------|-----|------|
| CVFCFF |     |     |      |     |      |
| Pearson Correlation | 0.896*** | 0.725*** | −0.309 | −0.686*** | −0.041 |
| \( R^2 \) | 0.803 | 0.526 | 0.095 | 0.470 | 0.002 |
| (Adj. \( R^2 \)) | (0.788) | (0.489) | (−0.026) | (0.429) | (−0.075) |
| F      | 53.014*** | 14.399*** | 1.368 | 11.537*** | 0.022 |
| N      | 15 | 15 | 15 | 15 | 15 |
| Linearity | Yes | Yes | No | Yes | No |

| CVFCFE |     |     |      |     |      |
| Pearson Correlation | 0.894*** | 0.677*** | −0.271 | −0.628** | 0.001 |
| \( R^2 \) | 0.800 | 0.459 | 0.073 | 0.395 | 0.000 |
| (Adj. \( R^2 \)) | (0.784) | (0.417) | (0.002) | (0.348) | (−0.077) |
| F      | 51.846*** | 11.012*** | 1.028 | 8.474** | 0.000 |
| N      | 15 | 15 | 15 | 15 | 15 |
| Linearity | Yes | Yes | No | Yes | No |

*** \( p \)-value < 0.01; ** \( p \)-value < 0.05; * \( p \)-value < 0.1.
Table 5: The results of data analysis for cluster 1

| CVFCFF Pearson Correlation | EVA | MVA | REVA | TVA | EEVA |
|-----------------------------|-----|-----|------|-----|------|
|                             | 0.097 | -0.459 | 0.212 | 0.052 | -0.323 |
| R²                          | 0.009 | 0.210 | 0.045 | 0.003 | 0.105 |
| (Adj. R²)                   | (-0.076) | (0.150) | (-0.029) | (-0.074) | (0.036) |
| F                           | 0.123 | 3.463 | 0.609 | 0.035 | 1.518 |
| N                           | 15   | 15   | 15   | 15   | 15   |
| Linearity                   | No   | No   | No   | No   | No   |
| CVFCFE Pearson Correlation | 0.069 | -0.208 | 0.218 | 0.096 | -0.188 |
| R²                          | 0.005 | 0.043 | 0.033 | 0.009 | 0.035 |
| (Adj. R²)                   | (-0.072) | (-0.030) | (-0.012) | (-0.067) | (-0.039) |
| F                           | 0.062 | 0.586 | 0.593 | 0.121 | 0.476 |
| N                           | 15   | 15   | 15   | 15   | 15   |
| Linearity                   | No   | No   | No   | No   | No   |

*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1.

first and second clusters cannot be generalized to companies presented in the third cluster. In sum, the results of tables 3, 4 and 5 suggest that in two of the three clusters, there was a significant correlation between EVA and TVA (as value-based performance indicators) and CVFCFF and CVFCFE (as the FCF-derived indicators), as well as between MVA and CVFCFE which are consistent with the findings in the earlier works of Kaviani (2013) and Kaviani et al. (2014).

5 Conclusion

Considering that on the stock exchange of each country the operating firms vary in certain aspects, such as production volume, line of activity, debt structure, growth opportunity, size, and financial and business risks, in future research, the ICA technique can be applied to evaluation of performance in the listed companies brought under in clusters based on their similarity compared to other clusters. The results of the study clearly indicated that economic profit based value-creating performance indicators convey information that has much to say about the FCF-derived indicators, so as the created value from FCF to a great extent can be explained by the former indicators. And these indicators can be utilized in the listed companies on Tehran Stock Exchange as reliable measures of value creation for shareholders, since they represent the actual return in terms of cash flow as compared to the required (rate of) return and the firm’s cost of capital. Also, in assessing the effect of capital project implementation on firm’s valuation, when the project is financed from equity, CVFCFE indicator should be used for measurement of the created value by the project, and if the project is financed from a combination of equity and...
loan, CVFCFF indicator should be used, since the obtained cash flow from the project is owned by shareholders and lenders and since the applied discount rate (weighted average cost of capital) depends on the risk of equity and debt. Hence, for future work on financial management and investment, use of the concepts and techniques produced in other scientific fields is highly recommendable by conducting reliable applied researches.

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