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Research Article

Market Valuation of High-Tech Companies in the IT and Automotive Industries: A Regression Analysis of Key Factors

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Abstract: The market value of a company is a key performance indicator for any modern business. The issue of market value growth is particularly relevant for high-tech companies, which serve as the leading drivers of digital economy development. Therefore, this study aimed to identify and analyze the key factors influencing the market value of high-tech companies. Using regression analysis tools and STATA 14.2 statistical software, econometric models were developed to describe the relationship between a company's market value and various influencing factors in two high-tech industries namely automotive and information technology (IT). To construct a multiple linear regression model, market capitalization was selected as the dependent variable (Y) while 15 indicators—including economic value added (EVA), equity capital, revenue, profit, number of employees, Research and Development (R&D) costs, goodwill, and intangible assets—were chosen as explanatory variables. Furthermore, this study was based on 10 years of panel data (2013–2022) from 25 listed automotive and IT companies each all of which were global leaders by market capitalization. Ordinary least squares regression models (OLS) with a high degree of fit were constructed for each industry. The results of the regression analysis showed that the models possessed high explanatory power with R-square values of 0.958 for the automobile industry and 0.921 for the IT industry. These figures suggested that 95.8% and 92.1% of the variance, respectively, could be explained and predicted by the obtained regression equations while avoiding issues of multicollinearity (strong linear dependence between independent variables) and heteroscedasticity in random errors. The study showed that the main common factors significantly impacting the market capitalization of high-tech IT and automotive companies were EVA and share price. However, R&D expenses and intangible assets were found to have no significant impact on market value of high-tech companies. Beyond the shared key factors, industry-specific factors influencing market capitalization were also identified for each sector. The high explanatory power of the obtained models allowed the framework to be used as an effective tool for managing, analyzing, and forecasting the value of IT and automobile companies.

Keywords: Company value factors; Eco-metric model; High-tech companies; Market value; Regression analysis

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1. Introduction

Companies in high-tech industries that spend the most on research and development (R&D) are becoming major forces driving the digital economy forward. The world's top R&D-investing sectors include three main areas namely ICT producers (computer hardware and electronics manufacturing), health industries (pharmaceuticals and biotechnology), and the automotive industry (Verevka et al., 2019). Therefore, this study focuses on high-tech companies in the automotive and information technology (IT) industries. During growing competition, high-tech companies are forced to rapidly intensify R&D efforts, continuously updating the products, and introducing fundamentally new technological solutions as well as global platforms. These innovations are becoming increasingly knowledge- and resource-intensive (Li, 2024; Aliu and Dedaj, 2023; Berawi, 2022; Park and Lee, 2022; Berawi, 2021), while companies compete with one another to maximize profitability.

According to the authors of the Global Innovation 1000 project, "there is no long-term correlation between the total amount of money that companies spend on supporting innovation programs and projects as well as the overall performance of the financial and economic activities" (Jaruzelski, 2024). Consequently, many studies assess a company's success based on market value (Demidenko et al., 2020; Zaytsev et al., 2020; Koller et al., 2020). An increasing company value indicates business growth, while a decline suggests operational challenges (Lazzari and Vena, 2025). Considering the objective characteristics, enterprise value serves as a key performance indicator for leading international companies across various industries and is a critical measure for investors (Yue et al., 2024; Chubuk and Zhukova, 2024). In addition to evaluating financial performance, companies should understand other factors that influence the value. Only by identifying these factors can businesses enhance their commercial viability and long-term sustainability.

The scientific literature contains numerous studies on the relationship between market value and various individual influencing factors. For example, publications on the impact of economic sustainability practices on market capitalization have produced mixed results approximately 30% of studies show a positive relationship, 14% a negative one, and the remainder report ambiguous results (Grishunin et al., 2023; 2022; Whelan et al., 2021). In some studies, a close connection can be traced between brand and company value (Kilian, 2009). An empirical study by Dosso and Vezzani (2019) showed a positive correlation between intellectual property and the dynamics of high-tech companies in the pharmaceutical, automotive, and IT industries (Dosso and Vezzani, 2019). The study by Ustinova and Ustinov (2014) considered the impact of intellectual capital on the capitalization of Russian industrial companies (Ustinova and Ustinova, 2014) while Berzkalne & Zelgalve focused on Baltic companies (Berzkalne and Zelgalve, 2014). Boiarko & Paskevicius further investigated the relationship between the market value of the company and market costs (Boiarko and Paskevicius, 2017). Sorescu (2012) and Zaytsev et al., (2020) analyzed the effect of innovation activity on the market value of specific economic entities. Furthermore, Stern emphasized the significant role of economic value added (EVA) in shaping enterprise market value (Stern et al., 2002).

Despite these studies, there is a lack of industry-specific publications as most analyses are cross-industrial. This gap makes the present study particularly relevant. There is currently no comprehensive comparative analysis of the factors influencing market value in the automotive and IT industries. Furthermore, no extensive empirical studies evaluate the impact of EVA and other factors on various performance indicators, including market capitalization. Theoretical studies on the nature of influencing factors remain limited.

This study aims to identify and analyze the key factors affecting the market value of high-tech companies. To achieve this objective, the analysis constructs econometric models including ordinary least squares (OLS), fixed-effects, and random-effects models to describe the relationship between company value and various cost factors in the automotive and IT industries. The study selects OLS models due to the following advantages.

- Unbiased Estimates: For large samples, OLS estimators are unbiased meaning the expected value equals the true value.
- Minimal Variance: OLS estimators have the lowest variance among all linear unbiased estimation methods.
- Ease of calculation and interpretation: OLS models are relatively simple to compute, and the relationships between dependent and independent variables can be visually interpreted through regression coefficients.

Developing OLS regression models for the IT and automotive industries allows for the identification of key drivers of market capitalization in these high-tech sectors, as well as a comparative analysis. Since industry-specific factors significantly influence company performance, a thorough assessment of market capitalization as a key performance indicator can help identify strengths, weaknesses, and opportunities for business growth and expansion.

2. Methods

2.1. Analysis of Existing Methods, Development of Algorithm, and Selection of Methodologies

Financial indicators served as fundamental measures of a company's financial position, providing investors and stakeholders with insights into the financial well-being (Kara et al., 2024). Multicriteria decision-making (MCDM) played a crucial role in solving multidimensional, complex problems in business and real-life scenarios (Lee et al., 2012). When analyzing a company's financial performance using the MCDM method, factors such as liquidity, profitability, turnover, financial leverage, and cash flow were considered. Additionally, various classical methods were used to analyze company value including the cost approach, and the income approach—incorporating models such as the DDM, FCFF, EVA (Su, 2024), RIM, APV, and DCF models (Kim-Duc and Nam, 2024)—and the market approach, which was applied in this study. Since market value calculations relied on the closing prices of listed companies, these figures fluctuated depending on changes in share prices (Cogliati et al., 2011).

To analyze the factors influencing company value, multiple regression analysis was employed. For instance, studies had previously used regression models to examine the correlation between brand value, market value, and total overseas sales of high-tech companies (Matsumura et al., 2019). Similarly, this study treated the market value of high-tech companies as the dependent variable, identified independent variables affecting market value, and constructed a regression model.

An econometric model was defined as a probabilistic-statistical framework describing the functioning of an economic or socio-economic system. A model was considered adequate when it accurately reflected the regularities of real-world processes with a sufficient degree of approximation accuracy (Ilyin and Levina, 2016). The regression model represented a subset of econometric models.

Regression analysis which was part of the primary tools in econometrics had been widely applied and adapted across interdisciplinary studies, as demonstrated in the work of Draper & Smith. In general terms, regression described and estimated the relationship between a given variable and one or more other variables. The variable under study was traditionally denoted as y, while explanatory variables were labeled as $x1$, $x2$, ..., xp. This method assumed that changes in the independent variables x influenced the dependent variable y.

This study used a linear regression model commonly used for predictive modeling. In this method, the dependent variable was continuous while the independent variables could be either continuous or discrete with the regression line being linear in nature. Linear regression aimed to find the best-fit straight line (also known as the regression line) to establish the relationship between the dependent variable y and one or more independent variables x. The equation for simple linear regression was as follows.

$$y_i = \alpha + \beta x_i + \varepsilon_i, \;\; i = 1,2, \dots, n \tag{1}$$

where y_i represented the dependent variable, x_i – was the independent variable, α and β – were the regression equation parameters, and ε_i – denoted the random variable.

Linear regression (equation 1) helped determine how independent variables influenced the dependent variable and allowed for future outcome predictions. In reality, economic and financial phenomena were rarely described by a single independent variable, multiple factors often influenced the dependent variable. Therefore, multiple regression analysis was necessary to resolve this situation showing the following form.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i, \;\; i = 1,2,\ldots,n \tag{2}$$

where y_i was the dependent variable, x_{i1}, x_{i2}, ..., x_{ip} – were the explanatory variables, β_1, β_2, ..., β_p – were the coefficients estimating the influence of explanatory variables, and εi represented a random variable.

A model with p variables assumed that these variables influenced the dependent variable. The coefficients β_1, β_2, ..., β_p showed the degree of influence of each factor on the dependent variable. In contrast to simple linear regression where each coefficient represented a direct effect, multiple regression coefficients were interpreted as partial regression coefficients. This implied that each coefficient reflected the partial influence of a given variable while holding all other variables constant. Multiple regression allowed for a more comprehensive analysis by examining the combined effects of several factors on an outcome. It was particularly useful for complex prediction and analysis, where multiple variables simultaneously influenced results.

Before performing regression analysis, correlation tests were conducted to assess the degree of correlation between independent (explanatory) variables and the dependent variable. This process helped determine whether statistically significant linear relationships existed between variables and measured the strength of these relationships.

Conducting a correlation test was an essential preliminary step before regression analysis. When no significant correlation was found between independent and dependent variables, the regression model would not yield useful predictive information. Conversely, when strong correlations existed these variables provided valuable insights in the model. The formula for calculating the linear correlation coefficient was as follows.

$$r_{xy} = \frac{\sum(x_i - \bar{x}) \times (y_i - \bar{y})}{\sqrt{\sum(x_i - \overline{x})^2 \times \sum(y_i - \overline{y})^2}} \tag{3}$$

where r_{xy} represented the correlation coefficient, $\bar{x}$ – was the mathematical expectation of series x, $\bar{y}$ was the mathematical expectation of series y.

Correlation tests typically used Pearson's correlation coefficient, which ranged between -1 and 1. The closer the coefficient's value was to ±1, the stronger the linear relationship between the variables. When the coefficient's value was close to 0, it indicated little to no linear relationship. The positive and negative signs of r_{xy} represented positive and negative correlations, respectively (Carlberg, 2016).

Linear regression models related to econometrics included OLS, fixed effects, and random-effects models. The OLS model was a technique for modeling data based on a linear predictive model. Its fundamental principle was to minimize the sum of squared errors between observed values and predicted values, ensuring the best fit for the linear model. The OLS model was based on the linear regression equations (1) and (2).

The fixed effects regression model (FEM) was a method for analyzing panel data. This approach allowed for comparisons between specific categories of independent variables and the interaction effects between these categories, while excluding other variables. Fixed effects regression accounted for variables in spatial panel data that varied across individuals iii but remained unchanged over time. The equation was expressed as follows (4).

$$Y_{it} = \alpha_i + X_{it}\beta + u_{it} \tag{4}$$

where Y_{it} was the observed value of the dependent variable for individual i at time t, X_{it} was the observed value of the independent variable for individual i at time t, β was the coefficient of the independent variable, α_i was the fixed effect representing the specific intercept for the individual I, and u_{it} was the error term.

In a linear regression model with fixed effects, only the intercept of the model changed across different time series while the slope coefficients remained constant. In contrast, a random-effects model treated the original (fixed) regression coefficients as random variables. The equation for this model was expressed as follows (5).

$$Y_{it} = \beta X_{it} + u_{it} + \epsilon_{it} \tag{5}$$

where Y_{it} was the dependent variable, X_{it} – was the independent variables, β was the coefficient of the independent variable, u_{it} was the individual effect which varied across individuals i but remained constant for the same i at different times t, ϵ_{it} was the error term, i – represented the individual, and t – denoted time.

In this model (equation 5), u_{it} was treated as a random variable that was generally assumed to be uncorrelated with X_{it} and normally distribution with a mean of zero. Equation (5) was useful for estimating correlations in time series or panel data. Random effects extended fixed effects by allowing for variability across individuals. When building models, both fixed-effects and random-effects models were considered and the Hausman test was used to determine which model best fit the data. When the test results indicated that the fixed-effects model provided a better fit, it was selected. However, the random-effecs model was used when there was no significant difference between the two.

2.2. Selection of Study Objects for the Regression Model and Industry-Specific Analysis

The study sample included high-tech companies from two industries namely the automotive and IT industries. Financial data for these companies were obtained from Macrotrends (Macrotrends, 2024), GuruFocus (Gurufocus, 2024), and company annual reports covering 10 years (2013-2022). The automotive industry was part of the largest and most profitable sectors worldwide with a high degree of technology and capital intensity. The industry remained a high-tech field due to advancements in digital technology with a long history of innovation. Table 1 presented a list of the top 25 largest automotive companies in the world ranked by market capitalization selected for the study (Companies Market Cap, 2024a).

Table 1 Largest Automotive Companies by Market Capitalization

Rating	Company name	Rating	Company name
1	Tesla (USA)	14	Mahindra & Mahindra (India)
2	Toyota (Japan)	15	Kia (South Korea)
3	BYD (China)	16	Great Wall Motors (China)
4	Mercedes-Benz (Germany)	17	Li Auto (China)
5	Ferrari (Italy)	18	SAIC Motor (China)
6	Volkswagen (Germany)	19	Suzuki Motor (Japan)
7	Stellantis (Netherlands)	20	Chongqing Changan (China)
8	BMW (Germany)	21	Renault (France)
9	Honda (Japan)	22	Isuzu Motors (Japan)
10	General Motors (USA)	23	Paccar (USA)
11	Ford (USA)	24	Nissan Motor (Japan)
12	Geely Automobile Holdings (China)	25	Mazda Motor (Japan)
13	Hyundai (South Korea)		

The information technology (IT) industry—also referred to as the information industry—focused on using information tools and technologies for collecting, organizing, storing, and transmitting data. It also provided various information services and technological solutions. The study included the 25 largest IT companies (Internet and software service providers) globally ranked by market capitalization as shown in Table 2.

Table 2 List of 25 largest IT Companies in the World Ranked by Market Capitalization (Companies Market Cap, 2024b; 2024c)

Rating	Company Name	Rating	Company Name
1	Microsoft (USA)	14	ServiceNow (USA)
2	Alphabet (USA)	15	IBM (USA)
3	Amazon (USA)	16	Uber (USA)
4	Meta Platforms (USA)	17	Booking Holdings (USA)
5	Tencent (China)	18	Automatic Data Processing (USA)
6	Oracle (USA)	19	Palo Alto Networks (USA)
7	Salesforce (USA)	20	Meituan (China)
8	SAP (Germany)	21	Airbnb (USA)
9	Netflix (USA)	22	MercadoLibre (Uruguay)
10	Alibaba (China)	23	Synopsys (Russia)
11	Adobe (USA)	24	Cadence Design Systems (USA)
12	Pinduoduo (China)	25	Equinix (USA)
13	Intuit (USA)		

2.3. Selection of Result and Factor Indicators for Building an Econometric Model Describing the Relationship Between Company Value and Cost Factors

The study selected market capitalization as the dependent variable (Y). Market capitalization represented the total value of the company's outstanding shares calculated based on stock market prices. Publications found a significant positive correlation between a high market value and industrial investment (Farooq et al., 2022). Companies with a high capitalization ratio typically operated with low external influence, becoming more independent and prosperous. These companies could reinvest the funds into future improvements to enhance operations. Additionally, capitalization growth helped attract investors increasing the volume of direct and portfolio investments.

Since the dependent variable Y (market capitalization) could be influenced by various financial and non-financial factors, we selected 15 independent variables to build a multiple linear regression model. These factors included EVA, equity, revenue, R&D costs, intangible asset value, number of employees, and others (Table 3). The EVA indicator was defined as the difference between net operating profit and the value of capital invested in the company (Verevka, 2018). The EVA model which showed the factors of value formation was expressed as follows (Equation 6).

$$EVA = NOPAT - WACC \times IC \tag{6}$$

where $NOPAT$ – represented the operating profit after taxes but before interest payments, $WACC$ – denoted the weighted average cost of capital, and IC – was the invested capital.

EVA measured a company's added value based on the funds it reinvested. In other words, a positive value indicated that the company generated sufficient profit after covering its capital investment. EVA also motivated companies to improve capital utilization efficiency, leading to superior value performance (Tortella and Brusco, 2003). Corporate R&D played a crucial role in high-tech companies, as the company allocated a significantly higher share of investment to research and development compared to other industries. Developing new products attracted consumers and enhanced competitiveness, eventually increasing company profitability. Therefore, examining the impact of this factor on company valuation was particularly important.

3. Results and Discussion

3.1. Preliminary data analysis

After selecting the study objects and independent variables, a model in the STATA software package was constructed using IT industry companies as an example. Table 3 presented a description of the selected indicators for IT companies. Next, the correlation between variables was considered particularly the relationship between independent and dependent variable Y.

The conducted correlation analysis showed that some factors did not follow a linear distribution. Combined with the results in Table 3, this outcome suggested the presence of outliers in the dataset. To address this issue, the next step included logarithmizing the variables to minimize the impact of extreme values.

Table 3 Descriptive Statistics of Variables

Name of the variable in the model	Average	Standard deviation	min	max
Market capitalization, $mn	221677.7	345624.5	690	2044480
EVA (Economic value added) , $mn	2452.286	8197.43	-31022.67	54290.47
Revenue, $mn	39930.92	69919.6	396.107	513983
Inventory, $mn	3052.435	6819.389	0.222	34405
Depreciation and Amortisation, $mn	3208.075	5240.927	11.835	41921
Equity capital, $mn	31450.21	48682.18	-5768	256144
Total current liabilities, $mn	17368.45	24128.6	206.102	155393
Number of Employees	89257.08	198201.7	1147	1608000
Inventory Turnover Ratio	7058.435	61294.75	2.653	537931
R&D expenses, $mn	5857.728	9792.176	40.888	73213
Return on investment (ROI), %	9.487317	19.49827	-127.1429	54.9665
Gross Margin, %	65.13839	18.49333	22.6	100
Goodwill and Intangible Assets, $mn	14525.99	17322.92	1.358	78822
Share price, USD/share	230.6892	387.5178	5.4	2393.209
Return on equity	20.04517	121.7009	-522.59	1677.108
Current assets as a share of total assets, %	45.60425	21.91879	1.148082	95.98169

After logarithmization, the distribution of each variable became linear. To further determine whether the relevant variables were related to the market capitalization of the dependent variable, an OLS model was constructed. The correlation analysis of the logarithmic form of the factors was presented in Figure 1.

Variables	lnMar~n	lnEVA	lnRev~e	lnInve~y	lnDep~n	lnto~l	lnTota~s	lnNu~s	Invent~o	lnR&~s	lnGoo~s	lnSha~e	ROI	Gross~n	Retur~y	Curre~s
lnMarket capitalization	1.000															
lnEVA	0.929	1.000														
lnRevenue	0.936	0.901	1.000													
lnInventory	0.698	0.686	0.810	1.000												
lnDepreciation, Amortisation	0.926	0.875	0.986	0.793	1.000											
lnto Equity capital	0.960	0.913	0.938	0.683	0.947	1.000										
lnTotal current liabilities	0.920	0.873	0.978	0.771	0.978	0.920	1.000									
lnNumber of Employees	0.776	0.741	0.924	0.846	0.902	0.766	0.913	1.000								
Inventory Turnover Ratio	0.122	0.107	0.123	0.080	0.111	0.156	0.077	0.041	1.000							
lnR&D expenses	0.896	0.859	0.943	0.867	0.939	0.914	0.887	0.843	0.155	1.000						
lnGoodwill and Intangible Assets	0.786	0.772	0.892	0.791	0.904	0.841	0.883	0.880	0.063	0.876	1.000					
lnShare price	0.166	0.052	0.103	0.285	0.068	0.006	0.091	0.184	-0.047	0.193	0.164	1.000				
ROI	0.159	0.367	0.110	0.162	0.018	0.014	0.086	0.096	-0.040	0.074	0.008	0.281	1.000			
Gross Margin	-0.612	-0.524	-0.682	-0.361	-0.679	-0.572	-0.726	-0.669	-0.078	-0.469	-0.464	-0.009	0.005	1.000		
Return on equity	0.068	0.245	0.212	0.221	0.136	-0.039	0.221	0.368	-0.092	0.057	0.221	0.197	0.655	-0.308	1.000	
Current assets as a share of total assets	0.256	0.319	0.255	0.172	0.209	0.314	0.221	0.098	0.132	0.270	0.142	-0.209	0.041	0.116	-0.128	1.000

Figure 1 Correlation Analysis After Logarithmization of Variables

3.2. Construction and Validation of OLS Model Conditions

The regression model constructed using STATA based on the raw values was presented in Table 4. From the regression results, the R^2 of the model was 0.944 and not significantly different from the adjusted R^2 indicating a high degree of model fit. The table also showed that not all variables had a significant correlation with Y, prompting some variables to be excluded. To identify variables for exclusion, we used a Variance Inflation Factor (VIF) test to check for multicollinearity among the variables. The final regression model was presented in Table 5.

The results presented in Table 5 indicated that after screening, five variables remained significant in the model with p-values less than 0.01, and there was no multicollinearity. Next, the linear relationship between the variables was examined. The following figure showed the relationship between the indicator and the regressor (Figure 2).

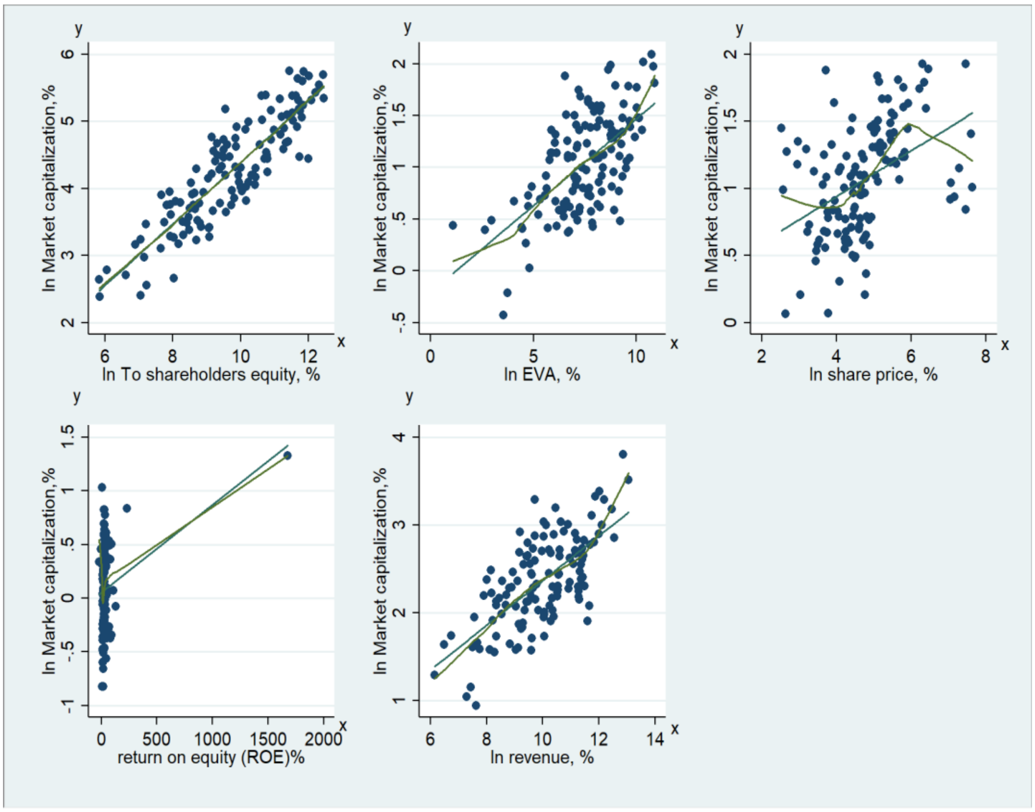

Figure 2 Checking the Linearity of the Relationship Between the Dependent and Independent Variables in the Selected OLS Model

Table 4 Construction of Regression Model Based on Raw Values

Market capitalization, $mn	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
EVA (Economic value added) , $mn	18.037	3.739	4.82	0	10.558	25.516	***
Revenue, $mn	8.041	2.962	2.71	0.009	2.116	13.965	***
Inventory, $mn	9.766	17.287	0.56	0.574	-24.813	44.346	
Depreciation and Amortisation, $mn	11.886	15.663	0.76	0.451	-19.445	43.217	
Equity capital, $mn	-0.296	1.3	-0.23	0.821	-2.896	2.304	
Total current liabilities, $mn	-1.277	3.04	-0.42	0.676	-7.357	4.804	
Number of Employees	-1.012	0.302	-3.35	0.001	-1.616	-0.407	***
Inventory Turnover Ratio	-0.062	0.268	-0.23	0.818	-0.597	0.473	
R&D expenses, $mn	-22.442	16.8	-1.34	0.187	-56.046	11.163	
Return on investment (ROI) %	4769.747	4846.186	0.98	0.329	-4924.069	14463.562	
Gross Margin, %	1315.021	1927.213	0.68	0.498	-2539.98	5170.022	
Goodwill and Intangible Assets, $mn	2.655	1.556	1.71	0.093	-0.458	5.768	*
Share price, USD/share	171.069	78.401	2.18	0.033	14.243	327.895	**
Return on equity	-3594.295	2038.565	-1.76	0.083	-7672.033	483.442	*
Current assets as a share of total assets, %	-2431.512	1243.072	-1.96	0.055	-4918.026	55.002	*
Constant	-637.832	153390.76	-0.00	0.997	-307465.04	306189.37	

Mean dependent var	394095.526	SD dependent var	502540.368
R-squared	0.944	Number of obs	76
F-test	67.982	Prob > F	0.000
Akaike crit. (AIC)	2022.392	Bayesian crit. (BIC)	2059.684

****** $p<0.01$, ** $p<0.05$, * $p<.1$*

As shown in Figure 2, the distribution of the variable "Equity" was very uniform and followed a normal distribution. However, the variables "Company Stock Price" and "ROE" were not evenly distributed with possible outliers. To further investigate, separate histograms of the market value variable's distribution were constructed which confirmed that in logarithmic form the distribution was symmetrical. The RESET test (Regression Equation Specification Error Test) was also constructed to check the model for missing explanatory variables. The result of RESET test was 0.015, rejecting the hypothesis that there were no missing variables in the model. The obtained value of hatsq exceeded 0.05, indicating that no missing variables with a quadratic term were present. Subsequently, the residuals and the homoscedasticity of the model were analyzed.

As shown in Figure 3, Alibaba's observation leverage was relatively high located in the upper left corner of the plot. This suggested that the data point exerted a relatively greater influence on the model despite having a low sum of squared residuals. Booking Holdings had lower leverage but a higher sum of squared residuals. However, due to its relatively low leverage, its influence on the model was minimal.

Table 5 Variant Regression Model After Screening

lnmarketcap	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
ln Equity capital	0.458	0.057	8.09	0	0.346	0.57	***
ln EVA	0.16	0.035	4.61	0	0.092	0.229	***
ln Share price	0.172	0.032	5.38	0	0.108	0.235	***
Return on equity	0.001	0	3.27	0.001	0	0.001	***
ln Revenue	0.255	0.068	3.77	0	0.121	0.389	***
Constant	2.78	0.315	8.82	0	2.156	3.404	***
Mean dependent var		11.797		SD dependent var		1.339	
R-squared		0.921		Number of obs		129	
F-test		287.299		Prob > F		0.000	
Akaike crit. (AIC)		124.743		Bayesian crit. (BIC)		141.902	

**** p<0.01, ** p<0.05, * p<0.1*

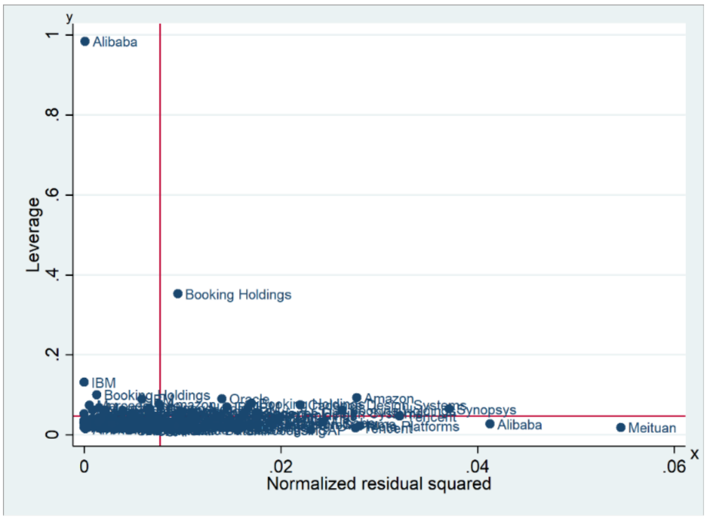

Figure 3 Residuals and Regression Leverage

The remaining companies, such as IBM, Amazon, and most others, clustered in the lower left corner of the graph. This indicated that the company had both low leverage and residuals, suggesting a good model fit for these data points with minimal impact on the regression results.

A Breusch-Pagan test was conducted to rule out heteroscedasticity which was a non-constant variance of the error terms (Gutman et al., 2022; Bolakale et al., 2021; Halunga et al., 2017). The results of this test were presented in Figure 4.

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lnmarketcap

         chi2(1)      =     0.01
         Prob > chi2  =   0.9386
```

Figure 4 Results of the Breusch-Pagan Test

The test results indicated that the p-value was 0.9386, which suggested the model was homoscedastic according to the Breusch-Pagan criterion, as the p-value exceeded the significance level of 0.05. Therefore, the null hypothesis was accepted, confirming no heteroscedasticity in the model. This implied that the error variance remained constant. Additionally, White's test corroborated that the residuals were homoscedastic. The density curve of the normally distributed random residual term was symmetrical, further supporting a normal distribution.

3.3. Selection of a Regression Model Using Panel Analysis

To determine the best regression model in addition to the OLS model, both fixed-effects and random-effects models were constructed. The OLS, fixed-effects, and random-effects aspects were compared to select the optimal model and the results were summarized in Table 6.

According to the results presented, some variables were non-significant in both the fixed-effects and random-effects models. All variables in the OLS model were significant, prompting the OLS model to be selected. Using the regression analysis of panel data from 10 years (2013–2022) for 25 listed companies in the IT industry, the significant economic factors affecting the market value of IT companies were identified while constructing the following regression model (Equation 7).

Table 6 Comparison of Regression Models

Variable		OLS	FE	RE
ln Equity capital		0.458***	0.103***	0.214***
ln EVA		0.160***	0.004	0.042**
ln Share price		0.172***	1.034***	0.745***
Return on equity		0.001 **	0	0.001**
ln Revenue		0.255***	0.089***	0.077
	year			
	2014		-0.062**	
	2015		-0.108***	
	2016		-0.143***	
	2017		-0.198***	
	2018		-0.247***	
	2019		-0.311***	
	2020		-0.357***	
	2021		-0.414***	
	2022		-0.377***	
_cons		2.779***	5.228***	5.037***

$$\ln(\mathrm{Y}) = 2.78 + 0.458\ln(\mathrm{X1}) + 0.16\ln(\mathrm{X2}) + 0.172\ln(\mathrm{X3}) + 0{,}001\ \mathrm{X4} + 0.255\ln(\mathrm{X5}) \quad (7)$$

where Y was the market capitalization, X1 – represented equity capital, X2 – denoted EVA, X3- was share price, X4 – served as return on equity (ROE), and X5 – indicated revenue.

Using the same methodology and algorithm, a regression model for the automotive sector was developed based on panel data from 10 years (2013–2022) for 25 listed automotive companies. The resulting model was given in Equation 8.

$$\ln(\mathrm{Y}) = 7.758 + 0.274\ln(\mathrm{X1}) + 0.369\ln(\mathrm{X2}) - 0.011\mathrm{X3} \quad (8)$$

where Y represented the market capitalization, X1 indicated EVA, X2 served as share price, and X3 denoted current assets as a share of total assets.

The regression analysis results showed that the models possessed high explanatory power. The R-squared value for the automotive industry model was 0.958, while for the IT industry model, it was 0.921. This indicated that 95.8% and 92.1% of the variance, respectively, could be explained and predicted by the resulting regression equations. Furthermore, the models avoided issues related to multicollinearity (strong linear dependence between independent variables) and heteroscedasticity of random errors. The constructed models effectively identified key factors influencing the market value of companies in the automotive and IT industries, a comparison of which is presented in Table 7. These models demonstrated that EVA and stock price were the common variables that simultaneously affected both industries. When EVA and stock price increased, the market capitalization of companies in both the IT and automotive industries also increased. This indicated that EVA and stock price were two crucial factors influencing the market value of high-tech companies in these industries.

Table 7 Comparison of Key Factors Influencing the Value of Companies in the IT and Automotive Industries

IT- industry	Automotive industry
EVA	EVA
Share price	Share price
Equity	Current assets as a share of total assets
Revenue	
ROE	

However, the regression models for the two industries included different variables. In the IT industry model, along with EVA and stock price, other significant factors influencing market capitalization were equity, ROE, and sales revenue. The amount of equity represented the real capitalization of a company and reduced investor risk. Therefore, companies with greater equity assets, all else being equal—tended to be valued more highly in the market (Peijie, 2023). Companies experiencing higher sales growth were more inclined to achieve higher market valuations, confirming the positive assessment investors assigned to growth performance. Moreover, companies with higher return on equity, a signal of efficiency and greater potential profitability, were rewarded with higher valuations in financial markets. This effect was reflected in the positive coefficient of return on equity, measured as the ratio of earnings to equity.

In contrast, the automotive industry model showed that a company's market value was influenced by the percentage of current assets relative to total assets. The negative effect of a higher ratio of current assets to total assets was statistically significant in this model due to the specific characteristics of the automotive industry. Traditional auto manufacturers faced increasing technological competition in the parts and components sector, as well as growing standardization, which shifted competitive advantages from auto brands to suppliers. These dynamics shortened process, operational, and financial cycles, while the introduction of just-in-time and MRP systems significantly increased inventory turnover rates. Consequently, the overall share of working capital in the industry declined.

These conclusions were supported by specific examples of enterprises. Companies with a higher share of working capital in their asset structure compared to the industry average—such as Renault Group, Nissan Motor, and Mazda Motor—experienced a more than threefold decline in market capitalization over the last 10 years. Additionally, the differences in regression models between the IT and automotive industries outlined certain structural characteristics, including the complexity and modularity of products, industry-specific technological frameworks, and variations in strategic and competitive behavior.

A seemingly paradoxical conclusion from this study was the insignificant impact of R&D expenses and intangible assets on the market value of high-tech companies. This finding supported the earlier hypothesis that the scale of R&D spending was not a guarantee of a company's success, as measured by its market capitalization growth. The results showed that in both the computer and automotive industries, markets did not necessarily reward companies for additional innovative assets. Furthermore, there was a possibility that markets might even penalize companies with exceptionally high R&D expenditures. For instance, Tesla's annual R&D spending doubled between 2020 and 2023, surpassing $3 billion, while its market capitalization was reduced by half over the same period.

Figures 5 and 6 showed that from 2013 to 2020, Microsoft's market capitalization and R&D investment tended to increase, while Tesla's market capitalization fluctuated significantly despite relatively stable R&D spending. From 2021 onward, although both companies continued to increase

R&D investment, the market capitalization began to decline, suggesting a lack of direct correlation between R&D investment and market value.

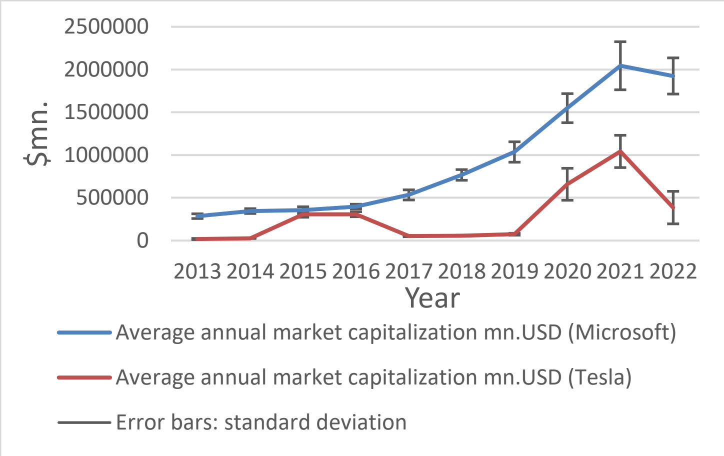

Figure 5 Dynamics of Market Value– Microsoft and Tesla

Since R&D investment might not yield immediate financial returns but remained crucial for long-term growth and innovation in high-tech sectors, it could cause cyclical fluctuations in the value of high-tech companies. Therefore, using the method proposed by Eremina and Rodionov (2023) which identified and corrected situational distortions in time series through data shifting and modification to determine the cyclical dominance of the modified series, the study attempted to add a lagged "R&D investment" variable to the regression model. Based on the normative efficiency coefficient for long-term investments in these industries, the R&D investment variable was lagged by four periods (four years) and was incorporated into the regression model. However, the results indicated that R&D expenditure remained insignificant and did not influence market value fluctuations in the long term.

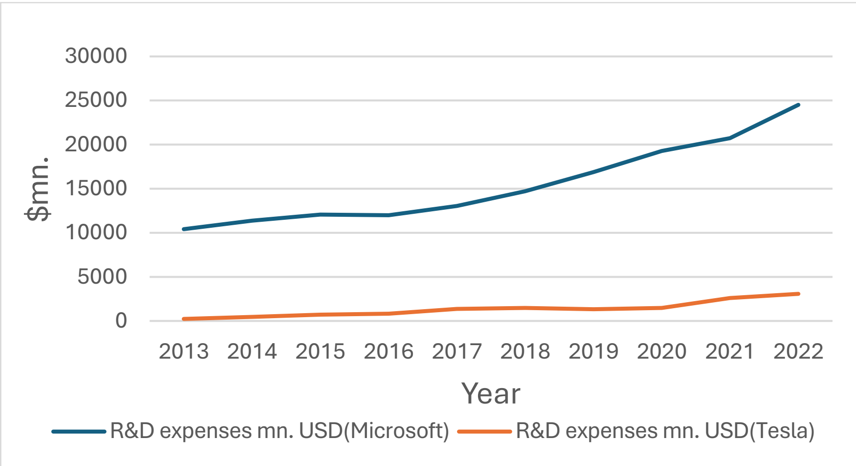

Figure 6 Dynamics of R&D Expenditures – Microsoft and Tesla

This conclusion correlated with results from other publications such as Kalantonis et al. (2020). The results also supported those of Chernova and Mikhaylova (2019), who examined the impact of internal R&D expenditure on the market capitalization of high-tech companies in the aerospace and defense industries. The study identified only a weak to moderate relationship between R&D costs and market capitalization. Therefore, the implementation of R&D costs did not automatically translate into an intangible asset that generated income.

However, there might be an indirect relationship between R&D expenditure and company value through revenue and profitability indicators. The introduction and launch of innovative products undoubtedly had a positive impact on market demand and stimulated sales, thereby increasing revenue, gross profit, ROE, and EVA. These indicators were included among the explanatory variables, and three were identified as key value drivers for IT companies, which did not contradict the findings of this study.

A similar situation was observed with important non-financial performance indicators of high-tech companies, such as customer satisfaction (discussed in more detail in Verevka (2018)). Increased customer satisfaction led to a growth in loyal customers, higher revenue and profit, and greater EVA. The limitation of this study to primarily financial indicators was not due to the prioritization over non-financial indicators, but rather to the lack of publicly available industry-wide data on non-financial indicators for high-tech companies, which prevented the creation of a sufficiently large sample for an objective study.

The lack of significance of intangible assets in valuation within the computer and automotive industries might also be related to the “dense network of overlapping intellectual property rights through which a company should cut its way to commercialize a new technology” (Shapiro, 2001), commonly referred to as a patent thicket. The existence of these barriers made it difficult to assess individual intellectual property rights in these complex industries (Heeley et al., 2007), and consequently to assess the direct impact on the market value.

4. Conclusions

In conclusion, the regression models developed for the IT and automotive sectors enabled the identification of variables that influenced the commercial value of a company, specifically its market capitalization. The study showed that EVA and stock price were the main factors that significantly impacted the value of successful high-tech IT and automotive companies. The observed differences in econometric models between the computer and automotive industries further confirmed the importance of industry-specific factors in determining value drivers. The developed regression models provided a powerful tool for strategic planning and value management in IT and automotive companies. The analysis offered valuable insights for developing a Balanced Scorecard (BSC) and facilitated effective decision-making in asset and capital management. The regression modeling approach used in this study could be applied to other high-tech industries, such as pharmaceuticals, biotechnology, aerospace, and defense. Therefore, future studies should focus on constructing models for additional industries to enable a more comprehensive comparative analysis of various high-tech sectors. This would eventually help identify common key value drivers across all high-tech companies, as well as specific factors unique to individual sectors within the high-tech economy.

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Author Contributions

Tatiana Verevka and Yuanxiang Gao equally contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

Conflict of Interest

The authors declared no conflicts of interest.

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