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Efficiency in Operations of NASDAQ Listed Technology Companies from 2011 to 2023

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Abstract: The performance of technology companies listed on NASDAQ significantly impacts larger economic trends. Investors need specific information to navigate market volatility and make informed decisions in an increasingly complex marketplace. Furthermore, amidst the ongoing digital revolution, legislators and regulatory agencies must comprehend the operational dynamics of technology companies to develop frameworks that support innovation while maintaining market stability. Our study assesses the impact on the overall operational efficiency of NASDAQ-listed firms from 2011 to 2023, resulting from the interdependence of critical variables such as selling, general, and administrative expenses (SGA), cost of goods and services sold (COGS), and investments in research and development (R&D). Johansen's cointegration methodology and pairwise Granger causality tests were employed to unveil long-term relationships, equilibrium adjustments, and causal relationships among the considered variables. The results provide critical insights into the strategic management of operational variables by the listed companies. The economic significance of the results obtained underscores the paramount importance of efficiently managing the cost of goods and services sold to achieve superior operating performance among these leading technology firms.

Keywords: operating efficiency; NASDAQ; co-integration studies; causality; performance

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1. Introduction

The National Association of Securities Dealers Automated Quotations (NASDAQ) stock market is home to some of the greatest innovative companies in the world. The companies included in the Nasdaq-100 index span various sectors, including consumer goods and services, industrials, healthcare, and technology. These holdings offer a means to invest in innovation and drive index performance[1]. The pursuit of excellence and continuous growth is crucial for these companies, requiring a comprehensive strategy that assesses operations by evaluating every cost driver to perform consistently and beyond expectations. Companies listed on the Nasdaq-100 index have led the technology and innovation space by maintaining a competitive advantage. These companies listed on the NASDAQ stock market have achieved and maintained this advantage over a longer time frame by employing effective management principles that go beyond conventional models.

Technology businesses are walking the path to increased efficiency and innovation through the complex interplay of workforce management and technological investments, with an emphasis on intangible assets and financial success. The significance of these interactions has gained importance due to the speed at which innovative technologies are being incorporated into their operations. Technology leaders influence the dual facets of their firms' financial health—both the bottom and top lines. By adeptly managing operations, they can elevate critical factors, including quality, variety, speed, reliability, and dependability. This contributes to the generation of augmented revenue streams. Cost reductions have been achieved within the operational framework by companies concentrating on control over selling general and administrative expenses (SGA), and substantial investments in cutting-edge research. Through strategic investments in advanced technologies and innovative methodologies, these companies have been successful in optimizing the efficiency of their workforce and streamlining production. Thus, by harmonizing top-line growth with bottom-line efficiencies, management could position their firms for sustained success in the ever-evolving landscape of technology-driven industries.

As firms navigate the competitive business landscape, the adoption of innovative technologies and practices emerges as a distinguishing factor for achieving sustainable growth (Ewert and Wagenhofer 2005; Foster and Gupta 1990; Fometescu and Hategan 2024; Prahalad and Hamel 1990). By managing technological advancements with strategic workforce management, companies can position themselves to thrive in a dynamic market, which can be assessed by evaluating parameters such as revenues, cost of goods and services sold, and the management of operating expenses (Barney 1991; Lev and Zarowin 1999; Nguyen and Ngo 2023). The anticipation of heightened sales and increased profitability is, thus, closely tied to the efficient operation of the firms, with effective cost management playing a pivotal role. One avenue through which firms can exert control over expenses is by incorporating cutting-edge and cost-effective technology into their production systems. By leveraging state-of-the-art technology, companies can streamline processes, enhance productivity, and reduce operational costs, ultimately contributing to improved profitability. Another strategic dimension involves the workforce, where the focus on productivity, innovation, and efficient utilization becomes paramount. Through innovative management practices, firms can unlock the full potential of their employees. This not only leads to increased output and quality but also ensures that human resources are deployed in the most efficient and effective manner possible.

Another crucial component of operating efficiency is the efficient control of SGA costs. Within these organizations, where creativity and adaptability are essential, SGA costs can play a major role in determining operating earnings in the short and long terms (Foster and Gupta 1990; Prahalad and Hamel 1990; Ewert and Wagenhofer 2005; Anderson et al. 2007; Fometescu and Hategan 2024). Reduced manufacturing costs can be achieved through strategic management of SGA, which will improve the company's total cost structure. Technology companies can direct resources toward essential functions, research and development, and other initiatives by optimizing SGA spending. In essence, the strategic control of SGA expenses in technology companies can lead to financial success by ensuring a balance between operational efficiency, innovation, and long-term profitability in a dynamic and evolving industry landscape (Kaplan and Norton 1996, 2001; Anderson et al. 2003; Subramaniam and Watson 2016). It is noteworthy that higher SGA expenses can, at times, be a strategic investment rather than a mere financial burden for technology companies. This is particularly true when these expenses are directed toward acquiring intangible assets that contribute to future operational efficiency and profitability (Anderson 1995; Banker et al. 1995). For instance, investments in research and development (R&D), employee training, or cutting-edge technology infrastructure may fall under SGA expenditures but can yield significant long-term benefits. When management deliberately increases SGA expenses with a focus on acquiring intangible assets, they may be positioning the company for improved manufacturing processes, enhanced product quality, or the development of innovative solutions (Balakrishnan et al. 2004; Ball et al. 2011). Strategic investments in intangibles, while reflected as higher current SGA expenses, can pave the way for future reductions in the cost of goods and services sold (COGS). The synergistic effect of these investments can ultimately lead to increased operational efficiency, reduced manufacturing costs, and improved competitiveness in the market (Balakrishnan and Gruca 2008; Grasso 2006; Ibrahim 2023). In such cases, higher SGA expenses can be viewed as a positive indicator of a firm's performance, signaling its commitment to innovation and future profitability (Datar et al. 1990; Horobet et al. 2021).

The variables considered are often examined individually to understand the operational efficiency of the companies. But, efficient management of SGA and R&D can be intricately tied to the COGS, creating a robust interdependence that demands strategic attention (Wernerfelt 1997; Zanjirdar et al. 2014). This dynamic relationship underscores the need for comprehensive cost management strategies that address both SGA expenses and COGS to optimize overall operational efficiency. Along with this, investments in R&D play a crucial role, driving innovation that can lead to the development of more cost-effective products or solutions, thereby influencing both SGA and COGS. Moreover, improvements in supporting departments, such as marketing and administrative functions, contribute to a leaner operational structure, directly impacting SGA.

Thus, our study investigates the operational effectiveness of technology businesses listed on the NASDAQ stock market during the period from 2011 to 2023 due to the interdependence of critical variables such as SGA, COGS, and investments in R&D. Thus, the economic significance of the study mainly lies in obtaining a broader understanding of the dynamics of cost management and financial performance within technology companies.

2. Data Collection and Methodology

Bloomberg provides access to reliable, real-time, and historical data for publicly traded companies. Bloomberg data were used as sources for our study. Based on the literature reviewed, quarterly data for the variables, namely sales, cost of goods and services sold (COGS), operating expenses (OExp), research and development (R&D) expenses, selling general and administrative expenses (SGA), and operating income (OInc) for each of the 100 companies listed in NASDAQ-100 were collected similar to the study conducted previously (Bhardwaj et al. 2021)[2]. Quarterly data were downloaded from Quarter 1, 2008 to Quarter 3, 2023. Upon screening the data for sufficiency, only 47 companies had complete data with respect to all the metrics. Among these companies, 25 technology-related companies were considered as shown in Table 1.

Table 1. List of the top 25 technology companies considered for study.

Sl. No	Companies	Sl. No	Companies
1	Adobe Inc. (ADBE)	14	IDEXX Laboratories, Inc. (IDXX)
2	Analog Devices Inc. (ADI)	15	KLA Corporation (KLAC)
3	Applied Materials Inc. (AMAT)	16	Lam Research Corp. (LRCX)
4	Activision Blizzard, Inc. (ATVI)	17	Microchip Technology Incorporated (MCHP)
5	ASML Holding NV (ASML)	18	Microsoft Corp. (MSFT)
6	Broadcom Inc. (AVGO)	19	Netflix Inc. (NFLX)
7	Cisco Systems (CSCO)	20	NVIDIA Corp. (NVDA)
8	Dexcom Inc. (DXCM)	21	Qualcomm Inc. (QCOM)
9	Electronic Arts Inc. (EA)	22	Skyworks Solutions Inc. (SWKS)
10	Fortinet Inc. (FTNT)	23	Texas Instruments Inc. (TXN)
11	Alphabet Inc. (GOOG and GOOGL)	24	Verisk Analytics, Inc. (VRSK)
12	Intel Corporation (INTC)	25	VeriSign, Inc. (VRSN)
13	Intuit Inc. (INTU)		

EViews University Edition 13 was used as the software for the analysis. We reviewed the autocorrelation that was present in the time series before conducting the analysis and eliminated the same. The Phillips–Perron unit root test was considered to understand the existence of stationarity in each time series. For each time series, we considered the lag length, depending on the condition of minimizing the Akaike information criteria (AIC) values for the indicators that were considered among the technology companies. Thus, the lag length was considered and selected by minimizing the AIC over different choices of the lag length. The values of AIC are computed as follows:

$$T\ log\ (RSS) + 2K$$

where T refers to the number of observations, K depicts the number of regressors, and the residual sum of squares is indicated by RSS.

Our research adopts Johansen's cointegration methodology developed by Johansen (1988) as an alternative and robust framework to delve into equilibrium price adjustments and ascertain long-run relationships within the context of technology companies. As articulated by Engle and Granger (1987), the presence of cointegration among a system of variables suggests that these variables are in a long-run equilibrium relationship. In essence, the application of Johansen's cointegration methodology serves as a powerful analytical tool to explore and understand the intricate dynamics among operating efficiency indicators within technology companies. This methodology goes beyond mere correlation by providing insights into the underlying economic forces that drive long-term relationships among these variables (Awad and Jayya 2013; Gao et al. 2018; Joshi and Beck 2024). By employing this approach, the study aims to uncover the level of integration among key operational metrics, shedding light on the interconnectedness and equilibrium aspects that define the operational efficiency landscape in the technology sector. We chose this method over various choices as it enables testing for the presence of more than one cointegrating vector (Johansen 1988, 1991; Johansen and Juselius 1990, 1992). Johansen's method was preferable and identifying the number of cointegrating vectors was possible via this method. The inferences drawn are based on the number of significant eigenvalues. We also found that, according to Banerjee and Carrion-i-Silvestre (2011), the alternative cointegration tests were found to have low power in comparison to Johansen's test. To check for stationarity arising from a linear combination of variables, the following AR representation for a vector VTS made up of n variables is used,

$$VTS_t = c + \sum_{i=1}^{s-1} \varphi_i Q_{it} + \sum_{i=1}^{k} \pi_i VTS_{t-i} + \varepsilon_t \tag{1}$$

where VTS is found to be, at most, I(1), Q_{it} represents the seasonal dummies (i.e., a vector of non-stochastic variables), and c is constant. It should be noted that not all variables that makeup VTS can be I(1). In order to find cointegration in the system, we only need two variables in the process to be I(1). However, if only two time series are examined (bivariate representation), then both have to be I(1). Thus, if the error–correction term is appended, then we have the following:

$$VTS_t = c + \sum_{i=1}^{s-1} \varphi_i Q_{it} + \sum_{i=1}^{k} \Gamma_I \Delta VTS_{t-i} + \Pi VTS_{t-k} + \varepsilon_t \tag{2}$$

The Equation (2) is basically a vector representation of Equation (1) with seasonal dummies added. In this equation, all long-run information is contained in the level terms, $VTS_{\text{t-k}}$, and short-run information is contained in the differences, ΔVTS_{t-i}. Equation (2) would have the same degree of integration on both sides only if 0 = Π (the series are not cointegrated). ΠVTS_{t-k} is (0), which infers cointegration. In order to test for cointegration, the validity of $H_1(r)$, shown below, is tested as follows:

$$H_i(r)\Pi = \chi\beta' \tag{3}$$

where b is found to be a matrix of cointegrating vectors, and g represents a matrix of error correction coefficients. The hypothesis, $H_1(r)$ implies that the process, ΔVTS_t, is stationary, VTS_t is nonstationary, and $\beta'\ VTS_t$ is stationary in nature (Johansen 1991). The results obtained using the Johansen method yield the trace and λ_{max} statistics, which allow determining the number of cointegrating vectors.

The present study also uses the Granger causality test to understand the direction of the causal relationship among the parameters identified. The test helps to determine whether changes in a parameter would have an impact on changes in other parameters. For this purpose, the modified linear Granger causality tests are employed. In order to assess the effects of the parameters on each other, the Granger causality test estimates the following model (Stoian 2008):

(a) The unrestricted model:

$$\Delta y_t^o = a + \sum_{i=1}^{P_o} b_i^o \Delta y_{t-1}^o + \sum_{j=1}^{k} \sum_{i=0}^{p_j} b_i^j \Delta y_{t-1}^j + \varepsilon_{1t}$$

where Δy_t^o denotes the first-order forward differences in the quarterly values of a parameter, and Δy_t^j denotes the first-order forward differences in the quarterly values of the other parameter.

(b) The restricted model:

$$\Delta y_t^o = a + \sum_{i=1}^{P_o} b_i^o \Delta y_{t-1}^o + \sum_{j \neq j_o}^{k} \sum_{i=0}^{p_j} b_t^j \Delta y_{t-1}^j + \varepsilon_{2t}$$

where, we exclude the particular parameter j_o.

The coefficients a, b_i^o and b_t^j are the parameters to be estimated in the regressions, and the orders P_o and P_j are the optimal lags. In order to test the significance of the effect of the particular parameter j_o on the movement of the other parameter, the F-statistic is employed, given by the following formula:

$$F = ((SSE_R - SSE_{UR})/(df_r - df_{ur}))/MSE_{UR} \tag{4}$$

Also, if the estimated lagged coefficient b_t^{jo} is statistically significant, then it can be inferred that changes in one parameter, j_o, cause changes in the movement of another parameter considered.

3. Data Analysis and Interpretation

Stationarity tests were conducted and examined for all the companies using the Phillips–Perron (P&P) test. It was observed that all the parameters were nonstationary without a trend (i.e., non-rejection of $\alpha_1 = 0$), and in most instances with a trend, which indicated the need for cointegrated methodologies (10% level was considered). The results obtained rejected the presence of drift ($\alpha_0 = 0$) rather than a trend ($\alpha_2 = 0$), which indicated the exclusion of a drift term. Thus, the data were found to be non-stationary for the time (Phillips and Perron 1988; Brenner and Kroner 1995; Doukas and Rahman 1987).

3.1. Johansen Tests for Cointegration Rank for Systems (Efficiency Indicators for all Technology Companies)

The results from conducting Johansen's method are presented in Tbale 2 and Tables A1–A6 in Appendix A. Before delving into the results for all 25 companies at once, Table 2 presents the summary of cointegration test results for Adobe Inc.

Table 2. The long-term relationship between sales versus operating efficiency indicators for Adobe Inc. (ADBE) using Johansen's cointegration methodology.

Company	Group	r	Trace	Critical Values (%)	Prob
Adobe Inc. (ADBE)	Sales vs. COGS	0	61.99 ***	25.87	0.0000
		1	9.08	12.52	0.1757
	Sales vs. OExp	0	61.22 ***	25.87	0.0000
		1	9.07	12.52	0.1762
	Sales vs. RD	0	65.01 ***	25.87	0.0000
		1	13.12 **	12.52	0.0396
	Sales vs. SGA	0	49.32 ***	25.87	0.0000
		1	7.37	12.52	0.3075
	Sales vs. OInc	0	55.31 ***	25.87	0.0000
		1	12.99 **	12.52	0.0416
	Sales vs. Efficiency Indicators	0	80.73 ***	69.82	0.0052
		1	44.99 *	47.86	0.0907
		2	20.78	29.80	0.3713
		3	9.71	15.49	0.3034
		4	2.47	3.84	0.1160

The optimal lag length for the Johansen cointegration method is obtained from an examination of the residual autocorrelation function of the cointegrating regressions. Critical values for the Johansen test are taken from the tables in Johansen and Juselius, 1990 paper. The ***, **, and * denote significance levels of 1 percent, 5 percent, and 10 percent, respectively.

The trace statistics, critical values, and p-values are reported. These are found to be basically likelihood ratio tests with the null hypothesis being $L_{T+1} = L_{T+2} = \ldots\ldots = L_P = 0$, indicating that the system has p-r unit roots, where r is the number of cointegrating vectors. Using the sequential approach, the rank was determined starting with the hypothesis of p-unit roots. If this is rejected, then the next hypothesis $L_2 = L_3 = \ldots\ldots = L_p = 0$ is tested, and so on. For each system, there can be, at most, $n-1$ cointegrating vectors (or common factors) that bind the assets in the system (with n being the number of time series in the system). For Adobe Inc., cointegration between sales and operating efficiency indicators displays one cointegrating vector for all variables, i.e., COGS, OExp, RD, SGA, and OInc.

Similarly, long-run relationships between sales versus operating efficiency indicators for the 24 remaining companies were analyzed; they are summarized in Tables A1–A6 and are shown in Appendix A. From Tables A1–A3, cointegration between sales and operating efficiency indicators, especially COGS, displays one cointegrating vector for all the companies, except for Analog Devices Inc., ASML Holding NV, Cisco Systems, Electronic Arts Inc., Intuit Inc., IDEXX Laboratories, Inc., KLA Corporation and Skyworks Solutions Inc. Similarly, in Tables A4–A6, co-integration between COGS and other efficiency indicators provides similar results. Co-integration studies between sales and operating expenses show the presence of one and two cointegrating vectors for most of the companies, except for Intuit Inc., IDEXX Laboratories, Inc., KLA Corporation, NVIDIA Corp, Skyworks Solutions Inc., Texas Instruments Inc., Verisk Analytics, Inc., and VeriSign, Inc. Co-integration between COGS and other operating expenses provides similar results.

If we consider cointegration between sales and R&D, we find the presence of one and two cointegrating vectors for most of the companies, except for ASML Holding NV, Intel Corporation, Intuit Inc., IDEXX Laboratories, Inc., NVIDIA Corp, Skyworks Solutions Inc., and Texas Instruments Inc. Similarly, co-integration between COGS and R&D provides similar results. When co-integration between sales and SGA is considered, we find the presence of one and two cointegrating vectors for most of the companies, except for ASML Holding NV, Broadcom Inc., Fortinet Inc., Alphabet Inc., Intel Corporation, IDEXX Laboratories, Inc., KLA Corporation, NVIDIA Corp, Skyworks Solutions Inc., Texas Instruments Inc., Verisk Analytics, Inc., and VeriSign, Inc. The co-integration between COGS and SGA provides similar results. Finally, when we consider co-integration between sales and operating income (OInc), we find the presence of one and two cointegrating vectors for most of the companies, except for Analog Devices Inc., Cisco Systems, Fortinet Inc., Intuit Inc., NVIDIA Corp, Skyworks Solutions Inc., and Texas Instruments Inc. Similarly, co-integration between COGS and OInc provides similar results.

3.2. Granger Causality Tests among Efficiency Indicators for All Technology Companies)

Based on Tables A7–A9 as shown in Appendix A, the Granger causality test results are summarized in Tables 3 and 4. Clearly, we observe that there is a one-way and two-way causal relationship between sales and other operating indicators. Notably, for a few companies, such as Activision Blizzard Inc., Cisco Systems, Dexcom Inc., Electronic Arts Inc., Alphabet Inc., Intel Corporation, Microsoft Corp, and Netflix Inc., bivariate causality exists between sales and other variables.

Table 3. Tabular representation of the causal relationship between sales and operating efficiency indicators for the first 13 companies (Adobe Inc. to Intuit Inc.) considered in the study.

Group	ADBE	ADI	AMAT	ATVI	ASML	AVGO	CSCO	DXCM	EA	FTNT	GOOGL	INTC	INTU
COGS and Sales			<--------	------->		<--------	------->	<------->	<--------		------->		
Oexp and Sales	<------->	------->	<------->	<------->	<------->	<------->	<------->	<------->	<------->	------->		<------->	------->
R&D and Sales	------->	------->	------->	<------->	------->	<------->	<------->	<------->	<------->	------->	<------->	------->	------->
SGA and Sales	<------->	<------->	<------->	<------->	<------->	<------->	<------->	<------->	<------->	------->	<------->	<------->	------->
Oinc and sales	<------->		<--------	<------->	<--------	<--------	<--------	<--------	<--------		<--------	<--------	

<------->, **------->**, **<--------** denote two-way, one-way (from right indicator to left), and one-way (from left indicator variable to right) causal relationships as per the significance levels, as shown in Tables A7–A9.

Table 4. Tabular representation of the causal relationship between sales versus operating efficiency indicators for all the remaining companies (IDEXX Laboratories, Inc. to VeriSign, Inc.) considered in the study.

Group	IDXX	KLAC	LRCX	MCHP	MSFT	NFLX	NVDA	QCOM	SWKS	TXN	VRSK	VRSN
COGS and Sales	<--------		<------->	<--------	<------->		------->	<--------	<--------	------->	<--------	<------->
Oexp and Sales	------->	------->	------->	------->	<------->	<------->		------->	------->	<------->	------->	<------->
R&D and Sales	------->	<------->	------->	<------->	<------->	------->	------->	<------->	------->	------->	<------->	------->
SGA and Sales	------->	------->	<------->	------->	<------->	<------->	------->	------->	------->	<------->	------->	------->
Oinc and sales		<------->			<--------	<------->	<--------	<--------	<--------	------->	<--------	

<------->, **------->**, **<--------** denote two-way, one-way (from right indicator to left), and one-way (from left indicator variable to right) causal relationships, as per the significance levels, as shown in Tables A7–A9.

A univariate one-way causal relationship was observed between operating efficiency parameters with sales in the majority of companies. A one-way causal relationship is observed between COGS with RD and SGA expenses. This implies that efficient management of COGS is more important, and if these expenses are managed well, it could provide technology companies with greater flexibility to achieve superior operating performance. For example, if companies deliberately increase SGA and RD expenses, it would lead to higher future operating profitability.

4. Discussion of the Results

Our study provides evidence that Nasdaq-listed technology companies adeptly manage operations by harmonizing top-line growth with bottom-line efficiencies, which is evident from the co-integration tests and Granger causality results. It is noteworthy that the variables are interdependent and there exists a dynamic interrelationship among them. The results show that the efficient management of selling, general, and administrative expenses (SGA) in technology companies is intricately tied to the cost of goods and services sold (COGS), creating a robust interdependence that has received more strategic attention among the companies (Chiosea and Hategan 2023). Thus, the need for comprehensive cost management strategies addressing SGA and R&D expenses with COGS to optimize overall operational efficiency is found to be the best option. Along with this, investments in R&D have significantly improved over the years in the companies considered. This underscores the importance of driving innovation, which has led to the development of more cost-effective products or solutions, thereby influencing both SGA and COGS. Thus, there is scope for future research to explore how improvements in supporting departments, such as marketing and administrative functions, can contribute to a leaner operational structure, directly impacting SGA.

5. Conclusions

In conclusion, our paper delves into the operational efficiency of the world's top technology companies, which are at the forefront of technological innovation. Leveraging quarterly data sourced from Bloomberg, our research focuses on key operational variables, including cost of goods and services sold, operating expenses, research, and development expenses, selling, general and administrative expenses, and operating income. Through the application of Johansen's cointegration and Granger's causality tests, the results provide critical insights into the strategic management of these operational components by successful technology companies. The findings underscore the paramount importance of efficiently managing the cost of goods and services sold to achieve superior operating performance among these leading technology firms. Johansen's cointegration methodology is employed to unveil long-term relationships and equilibrium adjustments among the considered variables. The results show the interplay among selected operational metrics, highlighting the interconnectedness and sustained relationships among them. The interconnectedness of operating efficiency indicators within technology companies suggests a strategic relationship that highlights how NASDAQ companies, and their management are exerting effective control over operating expenses, ultimately paving the way for higher future profitability. The findings underscore the notion that operating efficiency, as reflected in metrics such as COGS, plays a pivotal role in determining the success of technology companies. The economic significance of the results implies that judicious management of COGS can lead to superior operating performance, distinguishing successful technology firms in their ability to optimize resources and drive profitability.

From the Granger causality tests, we can conclude that SGA expenses exhibit bivariate causality with sales, signifying its pivotal role as one of the most influential cost drivers for technology firms. This underscores the importance of the strategic management of SGA expenses in achieving cost efficiency and future profitability. In the context of causality tests between COGS and other operating indicators, this study underscores that, for technology firms, the combined influence of COGS and SGA emerges as the most critical determinants of efficiency. This suggests that optimizing the cost structure through careful management of both COGS and SGA is paramount for technology companies aiming to achieve higher future profitability. As a forward-looking note, this paper highlights the potential for future research to extend these findings to other sectors, specifically exploring if the observed relationships hold true in industries such as industrial manufacturing, aerospace, and defense. This suggests a broader applicability of the study's insights and opens avenues for comparative analyses across diverse sectors, offering a comprehensive understanding of the operational dynamics that contribute to success in different industries. In essence, this paper provides a comprehensive analysis of the efficiency drivers within the top technology companies, showcasing the intricate relationships among key operational variables. The results not only contribute to the academic understanding of operational efficiency but also offer actionable insights for industry stakeholders seeking to navigate the complexities of the ever-evolving technology landscape.

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Data Availability Statement: The quarterly data for publicly listed NASDAQ companies were accessed from university version of Bloomberg. The data on various variables of 100 companies listed were downloaded from Quarter 1, 2008 to Quarter 3, 2023. Upon screening the data for sufficiency, among these companies, 25 technology-related companies were considered as shown in Table 1.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The long-term relationship between sales versus operating efficiency indicators for the first 10 companies (Adobe Inc. to Fortinet Inc., as presented in Table 1) using Johansen's cointegration methodology.

Group	r	(ADBE)	(ADI)	(AMAT)	(ATVI)	(ASML)	(AVGO)	(CSCO)	(DXCM)	(EA)	(FTNT)
Sales vs. COGS	0	61.99 ***	12.69	20.37 ***	38.57 ***	15.91	15.60 **	6.52	34.73 ***	11.37	10.53
	1	9.08	1.56	0.31	4.77 **	0.01	1.84	0.02	7.55 ***	0.08	0.62
Sales vs. OExp	0	61.22 ***	14.96 *	16.40 **	26.49 ***	12.12	34.99 ***	18.08 **	43.11 ***	21.08 ***	14.22 *
	1	9.07	5.83 **	0.33	3.973 **	0.27	2.41	0.71	11.91 ***	0.96	3.18 *
Sales vs. RD	0	65.01 ***	22.52 ***	16.40 **	44.74 ***	5.47	31.50 ***	18.03 **	43.57 ***	16.28 **	14.28 *
	1	13.12 **	6.09 **	0.48	16.78 ***	0.85	8.32 ***	0.73	13.86 ***	0.73	2.11
Sales vs. SGA	0	49.32 ***	14.95 *	27.24 ***	31.96 ***	9.61	13.11	20.38 ***	20.43 ***	31.87 ***	9.74
	1	7.37	4.81 **	0.44	3.00 *	0.00	1.78	0.18	3.02 *	1.32	1.52
Sales vs. OInc	0	55.31 ***	12.98	17.23 **	27.39 ***	15.29 *	26.89 ***	10.76	14.62 *	14.60 *	4.57
	1	12.99 **	3.80 *	0.45	7.28 ***	0.15	2.34	0.46	3.48 *	1.17	0.03
Sales vs. Efficiency Indicators	0	80.73 ***	97.84 ***	62.41	99.10 ***	57.58 ***	95.69 ***	85.59 ***	108.75 ***	98.59 ***	206.47 ***
	1	44.99 *	52.50 **	35.48	51.23 **	31.20 **	43.89	50.28 **	49.18 **	62.28 ***	113.91 ***
	2	20.78	25.50	12.54	19.22	9.55	23.03	27.39 *	24.14	35.60 ***	49.92 ***
	3	9.71	8.95	5.32	4.24	1.46	10.46	9.40	11.66	19.30 **	11.51
	4	2.47	0.46	0.68	0.01		0.07	1.93	0.64	5.32 **	2.04

The optimal lag length for the Johansen cointegration method is obtained from an examination of the residual autocorrelation function of the cointegrating regressions. Critical values for the Johansen test are taken from the tables in Johansen and Juselius's (1990) paper. Only trace values are provided in each column against the companies. The ***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A2. The long-term relationship between sales versus operating efficiency indicators for the other 10 companies (Alphabet Inc. to NVIDIA Corp., as presented in Table 1) using Johansen's cointegration methodology.

Group	r	(GOOGL)	(INTC)	(INTU)	(IDXX)	(KLAC)	(LRCX)	(MCHP)	(MSFT)	(NFLX)	(NVDA)
Sales vs. COGS	0	*16.45 ** *	*16.03 ** *	*4.40*	*9.18*	*9.26*	*15.49 ** *	*16.50 ** *	*24.37 *** *	*34.12 *** *	*16.28 ** *
	1	*0.57*	*0.02*	*1.58*	*1.28*	*0.96*	*0.17*	*2.62*	*6.15 ** *	*4.20 ** *	*4.19 ** *
Sales vs. OExp	0	*20.80 *** *	*16.63 ** *	*9.64*	*4.08*	*9.02*	*18.06 ** *	*23.87 *** *	*23.04 *** *	*16.01 ** *	*13.07*
	1	*3.47 * *	*0.14*	*0.83*	*0.21*	*1.76*	*0.68*	*7.28 *** *	*5.41 ** *	*0.78*	*3.87 ** *
Sales vs. RD	0	*28.45 *** *	*8.52*	*3.00*	*5.24*	*17.04 ** *	*14.72 * *	*24.19 *** *	*23.83 *** *	*28.69 *** *	*12.85*
	1	*1.54*	*0.29*	*0.39*	*0.05*	*2.76 * *	*4.51 ** *	*8.51 *** *	*10.30 *** *	*8.68 *** *	*3.97 ** *
Sales vs. SGA	0	*12.74*	*7.72*	*14.25 * *	*7.68*	*5.23*	*36.94 *** *	*20.47 *** *	*29.26 *** *	*17.90 ** *	*12.94*
	1	*2.80 * *	*0.28*	*0.52*	*1.35*	*0.97*	*2.06*	*3.86 ** *	*4.63 ** *	*1.67*	*3.65 * *
Sales vs. OInc	0	*13.43 * *	*14.44 * *	*5.22*	*17.79 ** *	*18.72 ** *	*14.70 * *	*17.40 ** *	*20.48 *** *	*19.80 ** *	*12.94*
	1	*2.70 * *	*0.02*	*0.20*	*1.29*	*1.71*	*1.18*	*3.07 * *	*4.20 ** *	*2.72 * *	*3.91 ** *
Sales vs. Efficiency Indicators	0	*100.79 *** *	*88.37 *** *	*115.56 *** *	*100.79 *** *	*85.09 *** *	*72.00 ** *	*68.92 * *	*124.79 *** *	*96.44 *** *	*95.66 *** *
	1	*56.72 *** *	*50.17 ** *	*73.80 *** *	*56.72 *** *	*32.43*	*39.97*	*37.74*	*65.99 *** *	*53.26 ** *	*49.76 ** *
	2	*23.11*	*25.73*	*40.28 *** *	*23.11*	*16.41*	*13.11*	*21.54*	*31.71 ** *	*22.29*	*28.32 * *
	3	*8.01*	*6.26*	*16.30 ** *	*8.01*	*6.34*	*5.48*	*6.68*	*14.24 * *	*6.51*	*14.71 * *
	4	*3.06 * *	*0.54*	*4.39 ** *	*3.06 * *	*0.22*	*0.05*	*0.65*	*0.76*	*1.72*	*5.82 ** *

The optimal lag length for the Johansen cointegration method is obtained from an examination of the residual autocorrelation function of the cointegrating regressions. Critical values for the Johansen test are taken from the tables in Johansen and Juselius's (1990) paper. Only trace values are provided in each column against the companies. The ***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A3. The long-term relationship between sales versus operating efficiency indicators for the remaining 5 companies (Qualcomm Inc. to VeriSign, Inc., as presented in Table 1) using Johansen's cointegration methodology.

Group	r	(QCOM)	(SWKS)	(TXN)	(VRSK)	(VRSN)
Sales vs. COGS	*0*	22.67 ***	7.96	13.76 *	29.69 ***	24.51 ***
	1	3.25 *	1.42	4.57 **	5.86 **	0.16
Sales vs. OExp	*0*	18.38 **	9.29	3.95	12.11	11.39
	1	2.24	1.43	0.06	4.10 **	3.43 *
Sales vs. RD	*0*	44.69 ***	8.67	6.35	22.43 ***	14.33 *
	1	13.69 ***	1.41	0.00	5.97 **	5.58 **
Sales vs. SGA	*0*	15.40 *	4.49	8.17	11.99	9.41
	1	1.44	0.22	1.70	4.02 **	4.04 **
Sales vs. OInc	*0*	17.28 **	7.64	3.70	16.70 **	18.2 **
	1	2.59	1.35	0.01	6.34 ***	1.30
Sales vs. Efficiency Indicators	*0*	78.85 ***	79.86 ***	93.55 ***	48.16 **	82.98 ***
	1	44.82 *	31.78	48.36 **	27.75 *	50.25 **
	2	20.21	14.32	26.26	12.43	22.23
	3	6.64	6.58	11.74	0.92	10.51
	4	0.00	0.37	1.14		3.94 **

The optimal lag length for the Johansen cointegration method is obtained from an examination of the residual autocorrelation function of the cointegrating regressions. Critical values for the Johansen test are taken from the tables in Johansen and Juselius's (1990) paper. Only trace values are provided in each column against the companies. The ***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A4. The long-term relationship between COGS versus operating efficiency indicators for the first 10 companies (Adobe Inc. to Fortinet Inc., as presented in Table 1) using Johansen's cointegration methodology.

Group	r	(ADBE)	(ADI)	(AMAT)	(ATVI)	(ASML)	(AVGO)	(CSCO)	(DXCM)	(EA)	(FTNT)
COGS vs. OExp	0	65.31 ***	9.55	37.74 ***	25.10 ***	12.02	31.22 ***	21.22 ***	42.60 ***	8.17	19.62 **
	1	9.18 ***	1.41	0.51	3.80 *	0.48	0.84	0.07	11.06 ***	1.29	2.96 *
COGS vs. RD	0	67.69 ***	18.11 **	29.88 ***	33.26 ***	4.90	29.58 ***	19.56 **	49.86 ***	15.86 **	18.41 **
	1	12.56 ***	1.36	0.65	11.43 ***	1.00	7.26 ***	0.02	13.44 ***	4.13 **	1.88
COGS vs. SGA	0	47.25 ***	8.67	19.30 **	20.81 ***	9.99	10.41	20.29 ***	18.25 **	7.72	13.28
	1	0.93	2.06	1.01	1.22	0.01	1.08	0.11	2.52	0.30	1.24
COGS vs. OInc	0	31.28 ***	10.93	16.50 **	32.38 ***	16.61 **	20.17 ***	4.45	11.87	12.41	3.98
	1	8.36 ***	1.47	0.29	9.50 ***	0.15	0.37	0.05	1.07	0.10	0.04

The optimal lag length for the Johansen cointegration method is obtained from an examination of the residual autocorrelation function of the cointegrating regressions. Critical values for the Johansen test are taken from the tables in Johansen and Juselius's (1990) paper. Only trace values are provided in each column against the companies. The ***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A5. The long-term relationship between COGS versus operating efficiency indicators for the other 10 companies (Alphabet Inc. to NVIDIA Corp., as presented in Table 1) using Johansen's cointegration methodology.

Group	r	(GOOGL)	(INTC)	(INTU)	(IDXX)	(KLAC)	(LRCX)	(MCHP)	(MSFT)	(NFLX)	(NVDA)
COGS vs. OExp	0	18.15 **	7.02	15.48	7.59	17.06 **	18.10 ***	25.15 ***	25.72 ***	33.49 ***	13.07
	1	4.03 **	0.83	1.39	0.11	0.47	0.23	9.04 ***	3.06 *	1.10	4.32 **
COGS vs. RD	0	16.80 **	9.83	6.15	10.02	22.70 ***	4.61	17.32 **	25.38 ***	45.93 ***	10.02
	1	0.01	0.25	1.10	2.18	0.48	0.58	5.05 **	8.81 ***	8.15 ***	3.35 *
COGS vs. SGA	0	20.27 ***	5.96	15.84 **	8.62	4.85	12.54	21.34 ***	30.50 ***	31.55 ***	13.43
	1	2.94 *	0.69	1.57	0.00	0.69	0.27	8.10 ***	5.14 **	3.48 *	4.18 **
COGS vs. OInc	0	18.15 **	9.24	6.39	13.42	7.63	13.14	13.63 *	21.31 ***	47.63 ***	11.93
	1	4.03 **	0.30	1.32	0.11	1.21	0.16	2.48	1.81	12.05 ***	4.23 **

The optimal lag length for the Johansen cointegration method is obtained from an examination of the residual autocorrelation function of the cointegrating regressions. Critical values for the Johansen test are taken from the tables in Johansen and Juselius's (1990) paper. Only trace values are provided in each column against the companies. The ***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A6. The long-term relationship between COGS versus operating efficiency indicators for the remaining 5 companies (Qualcomm Inc. to VeriSign, Inc., as presented in Table 1) using Johansen's cointegration methodology.

Group	r	(QCOM)	(SWKS)	(TXN)	(VRSK)	(VRSN)
COGS vs. OExp	0	17.64 **	26.24 ***	9.95	11.26	9.50
	1	5.20 **	1.88	0.08	1.31	0.09
COGS vs. RD	0	36.75 ***	16.39 **	8.49	15.21 *	12.23
	1	5.19 **	2.67	0.75	4.72 **	0.24
COGS vs. SGA	0	12.54	31.08 ***	14.21 *	11.66	6.77
	1	5.02 **	0.36	3.56 *	1.56	0.32
COGS vs. OInc	0	11.18	6.90	8.15	16.99 **	22.84 ***
	1	2.90 *	3.17 *	0.03	6.39 **	0.23

The optimal lag length for the Johansen cointegration method is obtained from an examination of the residual autocorrelation function of the cointegrating regressions. Critical values for the Johansen test are taken from the tables in Johansen and Juselius's (1990) paper. Only trace values are provided in each column against the companies. The ***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A7. Pairwise Granger causality between sales and efficiency indicators for the first 10 companies (Adobe Inc. to Fortinet Inc., as presented in Table 1).

Group	(ADBE)	(ADI)	(AMAT)	(ATVI)	(ASML)	(AVGO)	(CSCO)	(DXCM)	(EA)	(FTNT)
COGS does not Granger-cause sales	0.32	0.72	0.63	3.49 **	0.22	0.75	2.67 *	3.36 **	1.13	1.04
Sales do not Granger-cause COGS	0.55	0.63	2.48 *	0.70	1.16	5.34 ***	0.18	4.94 **	5.39 ***	2.16
OExp does not Granger-cause sales	23.14 ***	0.13 ***	1.51 ***	11.29 ***	2.34 ***	0.63 ***	0.14 ***	8.43 ***	0.65 ***	5.21 ***
Sales do not Granger-cause OExp	8.76 ***	2.17	6.63 ***	6.19 ***	5.68 ***	17.67 ***	2.82 *	4.94 **	9.05 ***	0.71
RD does not Granger-cause Sales	23.95 ***	2.37 ***	4.01 ***	12.86 ***	1.86 ***	4.52 ***	1.54 ***	9.91 ***	1.13 ***	5.93 ***
Sales do no Granger-cause RD	0.17	1.87	1.33	9.52 ***	0.38	4.32 **	5.21 **	3.66 **	6.34 ***	0.96
SGA does not Granger-cause sales	19.15 ***	1.96 ***	3.77 ***	9.95 ***	1.09 ***	1.40 ***	3.89 ***	0.16 ***	1.24 ***	1.72 ***
Sales do not Granger-cause SGA	10.47 ***	4.83 **	10.73 ***	9.86 ***	4.26 ***	3.47 **	4.90 **	3.24 *	15.48 ***	1.82
OInc does not Granger-cause sales	8.84 ***	0.10	1.11	6.42 ***	2.09	0.18	0.23	0.14	0.31	1.77
Sales do not Granger-cause OInc	4.15 **	2.01	10.26 ***	6.86 ***	7.69 ***	7.96 ***	3.35 **	3.37 **	2.81 *	2.05

***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A8. Pairwise Granger causality between sales and efficiency indicators for the other 10 companies (Alphabet Inc. to NVIDIA Corp., as presented in Table 1).

Group	(GOOGL)	(INTC)	(INTU)	(IDXX)	(KLAC)	(LRCX)	(MCHP)	(MSFT)	(NFLX)	(NVDA)
COGS does not Granger-cause sales	4.77 **	0.58	1.11	0.07	2.36	4.09 **	0.93	3.26 *	2.22	8.27 ***
Sales do not Granger-cause COGS	1.24	0.27	1.70	2.57 *	1.22	3.47 **	4.51 ***	7.89 ***	2.15	1.67
OExp does not Granger-cause sales	5.43 ***	0.66 ***	1.53 ***	0.05 ***	0.26 ***	2.84 ***	0.97 ***	0.84 ***	5.30 ***	0.28 ***
Sales do not Granger-cause OExp	2.08	3.57 **	1.47	0.41	2.28	0.58	1.92	7.19 ***	2.96 *	1.24
RD does not Granger-cause Sales	10.58 ***	0.22 ***	0.67 ***	0.15 ***	3.43 ***	2.96 ***	0.03 ***	1.37 ***	5.66 ***	0.68 ***
Sales do not Granger-cause RD	4.39 **	1.71	0.42	0.65	5.36 ***	1.80	2.82 *	3.58 **	0.39	0.98
SGA does not Granger-cause sales	6.55 ***	2.35 ***	1.90 ***	0.07 ***	1.25 ***	14.81 ***	1.81 ***	5.88 ***	4.88 ***	0.92 ***
Sales do not Granger-cause SGA	6.01 ***	3.07 *	0.71	2.15	0.82	7.83 ***	0.08	2.67 *	4.25 **	1.50
OInc does not Granger-cause sales	2.27	0.46	0.61	0.08	4.00 **	1.93	1.45	0.54	3.20 *	0.20
Sales do not Granger-cause OInc	4.94 **	5.37 ***	2.28	0.61	7.71 ***	1.24	0.07	5.83 ***	3.40 **	2.62 *

***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A9. Pairwise Granger causality between sales and efficiency indicators for the remaining 5 companies (Qualcomm Inc. to VeriSign, Inc., as presented in Table 1).

Group	(QCOM)	(SWKS)	(TXN)	(VRSK)	(VRSN)
COGS does not Granger-cause sales	2.19	0.99	2.94 *	0.77	4.24 **
Sales do not Granger-cause COGS	3.32 **	3.61 ***	2.00	9.09 ***	3.70 **
OExp does not Granger-cause sales	0.68 ***	3.27 ***	4.70 ***	0.66 ***	0.49 ***
Sales do not Granger-cause OExp	1.02	1.97	8.18 ***	1.95	2.86 *
RD does not Granger-cause sales	2.97 ***	0.22 ***	2.63 ***	1.20 ***	1.44 ***
Sales do not Granger-cause RD	15.32 ***	2.24	1.95	7.73 ***	0.99
SGA does not Granger-cause sales	0.06 ***	0.40 ***	9.58 ***	0.60 ***	0.69 ***
Sales do not Granger-cause SGA	0.69	1.09	6.76 ***	1.88	0.00
OInc does not Granger-cause sales	0.73	2.27	6.36 ***	0.58	1.73
Sales do not Granger-cause OInc	2.65 *	7.52 ***	0.88	4.60 **	1.48

***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A10. Pairwise Granger causality between COGS and efficiency indicators for the first 10 companies (Adobe Inc. to Fortinet Inc., as presented in Table 1).

Group	(ADBE)	(ADI)	(AMAT)	(ATVI)	(ASML)	(AVGO)	(CSCO)	(DXCM)	(EA)	(FTNT)
OExp does not Granger-cause COGS	27.69 ***	0.72	1.87	6.42 ***	2.02	0.72	0.06	10.70 ***	2.78 *	7.35 ***
COGS does not Granger-cause OExp	9.53 ***	1.37	2.65 *	6.86 ***	5.29 ***	12.51 ***	6.77 ***	6.27 ***	0.25	1.17
RD does not Granger-cause COGS	28.08 ***	1.14	5.78 ***	11.94 ***	1.59	4.37 **	0.21	14.90 ***	7.42 ***	7.93 ***
COGS does not Granger-cause RD	0.15	0.68	0.33	13.27 ***	0.00	4.76 **	5.19 **	4.30 **	0.67	1.91
SGA does not Granger-cause COGS	22.29 ***	0.82	3.72 **	7.68 ***	1.91	2.51 *	0.09	0.99	1.74	3.11 *
COGS does not Granger-cause SGA	11.42 ***	2.38	4.03 **	3.08 **	3.68 **	1.84	2.59 *	0.98	0.08	1.25
OInc does not Granger-cause COGS	7.08 ***	0.53	1.81	3.84 **	2.04	1.02	0.13	0.44	1.74	1.12
COGS does not Granger-cause OInc	2.74 *	2.57 *	9.18 ***	8.07 ***	7.56 ***	4.36 **	0.98	2.99 *	0.98	1.30

***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A11. Pairwise Granger causality between COGS and efficiency indicators for the other 10 companies (Alphabet Inc. to NVIDIA Corp., as presented in Table 1).

Group	(GOOGL)	(INTC)	(INTU)	(IDXX)	(KLAC)	(LRCX)	(MCHP)	(MSFT)	(NFLX)	(NVDA)
OExp does not Granger-cause COGS	4.66 **	0.47	0.64	2.03	0.97	5.15	2.24	2.98 *	2.18	1.79
COGS does not Granger-cause OExp	6.89 ***	2.02	1.01	0.04	6.15 ***	3.13 *	1.29	8.61 ***	8.00 ***	5.49 ***
RD does not Granger-cause COGS	3.90 **	0.57	0.42	5.69 ***	0.52	0.20	4.36 **	3.85 **	0.84	0.13
COGS does not Granger-cause RD	9.97 ***	1.51	0.88	4.99 **	10.39 ***	0.04	1.08	3.32 **	0.10	3.19 *
SGA does not Granger-cause COGS	4.07 **	0.88	0.22	0.99	0.68	3.20 *	5.08 **	9.14 ***	1.81	2.14
COGS does not Granger-cause SGA	9.65 ***	1.77	0.42	0.78	0.72	2.46	1.14	0.55	7.71 ***	3.50 **
OInc does not Granger-cause COGS	1.49	0.34	0.36	2.56 *	0.52	2.32	0.53	0.62	3.72 **	0.29
COGS does not Granger-cause OInc	3.35 **	3.87 **	0.25	1.03	1.53	1.32	0.18	7.62 ***	2.97 *	3.77 **

***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Table A12. Pairwise Granger causality between COGS and efficiency indicators for the remaining 5 companies (Qualcomm Inc. to VeriSign, Inc., as presented in Table 1).

Group	(QCOM)	(SWKS)	(TXN)	(VRSK)	(VRSN)
OExp does not Granger-cause COGS	3.08	1.99	4.84 **	2.43	0.25
COGS does not Granger-cause OExp	0.01 ***	12.75 ***	10.33 ***	2.28	2.35
RD does not Granger-cause COGS	3.43 **	0.70	1.68	0.97	0.46
COGS does not Granger-cause RD	15.78 ***	1.48	2.32	4.28 **	4.46 **
SGA does not Granger-cause COGS	0.81	6.27 ***	3.48 **	2.29	1.07
COGS does not Granger-cause SGA	1.01	1.15	2.82 *	2.29	0.47
OInc does not Granger-cause COGS	2.18	1.13	8.65 ***	4.87 **	3.87 **
COGS does not Granger-cause OInc	1.61	2.90 *	3.31 **	3.81 **	1.65

***, **, and * denote significance levels of trace levels at 1 percent, 5 percent, and 10 percent, respectively.

Notes

1. https://www.nasdaq.com/solutions/nasdaq-100/companies (accessed on 14 November 2023).
2. Anderson et al. (2007) examined that, the efficient management of selling, general, and administrative expenses (SGA) is closely tied to the Cost of goods and services sold (COGS) within technology companies. This dynamic relationship necessitates strategic attention to both aspects of cost management to optimize overall operational efficiency. Additionally, investments in Research and Development (R&D) play a pivotal role in driving innovation and product development, thereby influencing both SGA and COGS. (accessed on 21 December 2022).

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