RESEARCH ARTICLE

Cointegration Analysis of the Performance of Semiconductor Manufacturers by Leveraging the Trend of Big Technology Companies

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ABSTRACT: In this study, we evaluate the interrelationship between the performance of major technology companies and semiconductor manufacturers during an unstable economic cycle using Johansen's cointegration test. Recent market instability in the semiconductor industry, stemming from the COVID-19 pandemic and a global trade war, has impacted the semiconductor supply chain across the US, the EU, and Asia. We hypothesize that this environment led to an alignment in the performance between the chipmakers and the technology companies that are their primary consumers. Based on a technical analysis of stock indicators, Johansen's cointegration test was employed to evaluate the extent of the relationship between their respective stock trends. Our findings reveal a strong relationship between the stock trends of technology and semiconductor companies, particularly when these trends are measured by price momentum (the strength or speed of price movement). This suggests that cointegration in the chip market becomes stronger in the short term, primarily influenced by price momentum rather than long-term trading fluctuations or price changes driven by external macroeconomic factors.

KEYWORDS: Systems Software, Languages and Operating Systems, Cointegration Analysis, Technical and Statistics.

Introduction

Semiconductors are a solid material that has a unique electrical conductivity between that of metallic conductors and organic insulators, making them essential for creating integrated circuits and other electronic components.[1] The semiconductor industry is fundamental to driving technological innovation.[2] Devices such as smartphones, computers, electric vehicles, and even household appliances rely on semiconductors for processing power, connectivity, and user interface.

From 2019 to 2024, and continuing to the present, the semiconductor industry has faced significant disruptions due to the COVID-19 pandemic.[3,4] In addition, recent developments in intellectual property protection and geopolitical interventions—such as trade wars—have severely impacted global chip production, leading to shortages, supply chain disruptions, and pricing volatility.[4,5] In particular, the U.S.–China trade war has undermined the stability of the global chip supply chain through export restrictions, sanctions, and efforts by both countries to repatriate manufacturing.[5] This recent economic conflict has prompted economists and policy analysts to reconsider the importance of the relationship between chipmakers and technology companies as chip consumers.[6] Therefore, developing a method to evaluate this interrelationship is essential for understanding the current trend of the chip industry and for forming reliable expectations of the future chip cycle. In this study, we aim to establish a framework for assessing this relationship through the stock trends of semiconductor companies.

In the empirical analysis, three representative chipmakers and three major technology firms are selected to serve as proxies for semiconductor manufacturers and consumers, respectively. The selected chipmakers are Samsung Electronics, SK Hynix, and Taiwan Semiconductor Manufacturing Company, while the consumers are Apple, Lenovo, and NVIDIA. These companies are chosen for their market leadership in the global technology and semiconductor industry, based on regular reports.[7,8] We first analyze their stock trends using technical indicators and then apply the Johansen cointegration test. The technical analysis is applied to the stock markets for visual clarity of price trends and movements, which helps identify trend patterns with entry and exit points.[9] Johansen cointegration is used as the key methodological approach to estimate the extent of the interrelationship among multiple time series variables.[10]

In this study, the selection of stock indicators is critical, as employing a diverse set that captures different dimensions of market behavior allows for more meaningful and reliable results while enhancing the robustness of the analysis. There are several stock indicators, such as trend, momentum, and volatility indicators, to estimate the interrelationship between two industries. Each indicator, however, provides distinct dimensions of market behavior, as shown by long-run co-movements, short-term dynamics, and risk-related fluctuations, respectively. When combined, they complement one another and strengthen the robustness of correlation analysis.

Importantly, we assume that while uncertainty escalates in the semiconductor market for a short period, the stock price movements of big tech companies and chipmakers are expected to be linked. However, this connection would weaken over time due to market resilience and the drive to maintain a balance between supply and demand. This expectation is reasonable if considering the conventional wisdom for the macroeconomic cycle. Raunig and Houari claim that there is no transmission

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mechanism to reveal the complexity and potential negative impact during the shock wave from business uncertainty cycles.[11,12] And the precise linkage between the unstable stock market and macroeconomic aggregate demands has not been well understood. Therefore, our study would provide a pathway to understand the market elasticity in the semiconductor industry for both suppliers and demanders during periods of economic instability.

Methods

In this study, we employed a two-fold approach to investigate the interrelation between the performance of chip manufacturers and major technology companies as their primary consumers. First, we applied technical analysis to assess each company's stock performance, including its price movement and trading volume.[13,14] Second, we applied Johansen's cointegration test to evaluate the strength and extent of the relationships among the variables derived from the technical analysis. The technical analysis helped us identify patterns and trends in stock charts, which differ from fundamental analysis, which focuses on intangible factors such as a company's financial health. Johansen's cointegration test is a robust method for analyzing relationships among multiple time series variables, yielding meaningful insights into long-term relationships. This test has various applications for multivariate analyses such as portfolio management, forecasting, and financial modeling.[10] In this context, a "time series" refers to continuous observations over a specific period of time.

Figure 1 illustrates the flowchart of the research process we applied, which outlines the sequence of the technical analysis and the Johansen cointegration test, with the arrows and boxes indicating the workflow and the sub-processes for each step, respectively. The analysis was performed based on the Python scripts of Google Colab, a free, cloud-based Python notebook environment provided by Google.[15] The scripts are shared in the link.[16]

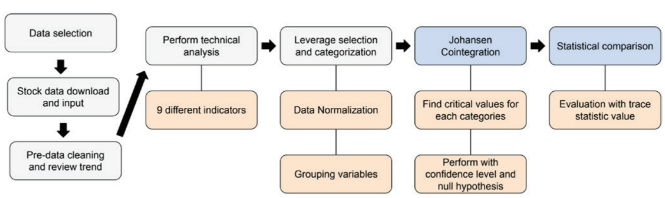

Figure 1: A flowchart of the overall analysis applied in this study. The primary analysis consists of the technical stock analysis and Johansen cointegration test, with a gray and light blue background, respectively. The sub-processes are indicated with an orange background. The arrows indicate the direction of the workflow. The process was irreversible, but parallel for each variable. This flow chart provides an easy guideline of the entire process applied in this study.

The three major semiconductor manufacturing companies for chipmakers and the three leading technology companies as semiconductor consumers are selected for this study.[7,8] The semiconductor manufacturers are Samsung Electronics Co., Ltd (SE: 005930.KS), SK Hynix Inc. (000660.KS), and Taiwan Semiconductor Manufacturing Company Limited (TSM), all known for producing memory and system chips. The tech companies are Apple Inc. (AAPL), Lenovo Group Limited (LNYGY), and NVIDIA Corporation (NVDA). Samsung and SK are listed and traded on the Korea Composite Stock Price Index (KOSPI). In contrast, TSMC, AAPL, LNYGY, and NVDA are traded in American Depositary Receipts (ADRs) on the New York Stock Exchange (NYSE) and the Nasdaq Stock Market (NASDAQ).[8]

Different from the usual economic cycles, the recent instability in the semiconductor sector is supposed to be driven by COVID-19 and geopolitical tension.[3] It seems to be closely linked to strategic competition over emerging technologies like artificial intelligence (AI) and military systems.[4,5] To properly reflect these factors, we analyzed the stock trends of the above companies from January 2, 2019, to December 30, 2024, assuming that this time period captures the dynamics of the global semiconductor conflict.[3] We believe that the relationship between chip manufacturers and chip consumers would become sensitive amid these intensified economic tensions, and it can evaluate the impact of how the performance of the chip-consuming companies influences the market performance of chip manufacturers.

Technical Analysis:

We downloaded the stock trend dataset of our selected companies from Yahoo Finance, which has open, high, low, close, and adjusted close prices.[8] The data was then imported into a Google Colab script for the analysis. During the pre-processing stage, we cleaned the data by removing entries from non-trading days (e.g., holidays and weekends) and periods with anomalous activity caused by extreme volatility or regulatory events. After that, the overall trends were presented as the candlestick chart, as shown in Figure 2. For the technical analysis, we utilized nine different indicators, which are derived from different mathematical models to characterize the various market behaviors. Table 1 describes the features of the indicators applied. The detailed definition and application of the technical indicators are well described in the literature.

Table 1: Brief description of the advantages and disadvantages of the stock indicators applied in this study. From the table (Table 1), one can easily compare the characteristics of the stock indicators for the analysis.

Category	Examples	Advantages	Disadvantages
Trend Indicator (Describing the direction and strength of a trend.)	Simple moving average (SMA), Exponential moving average (EMA), Moving average convergence divergence (MACD)	- Capture long-term price direction and structural co-movements - Filter out short-term noise, useful for equilibrium analysis	- Lagging in nature, less responsive to sudden shocks - May distort short-run correlations
Momentum Indicator (Presenting the speed of price changes)	Relative strength index (RSI), Stochastic Oscillator (SO)	- Measure speed and intensity of price changes - Detect short-term lead–lag relationships and asymmetric responses	- Highly sensitive to noise, risk of spurious correlations - Focused on short-term fluctuations rather than long-term equilibrium
Volatility Indicator (Describing the magnitude of a stock's price movement)	Bollinger Bands	- Reflect the magnitude of price fluctuations - Capture co-volatility during crises or uncertainty	- Lack directional information - Sensitive to extreme values, may overstate correlations

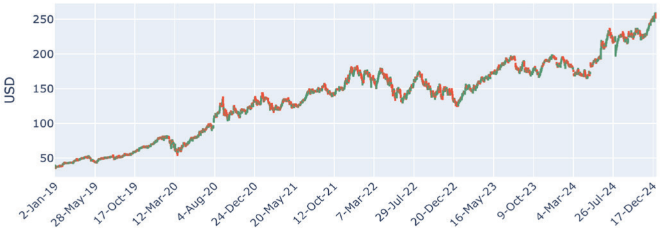

Figure 2: A candlestick chart of Apple Inc. (AAPL) during the selected period, from Jan. 2, 2019, to Dec. 30, 2024. This chart represents the overall price movement of a stock for open, high, low, and close (OHLC). It exhibits the increase in overall prices as the date progresses. Some of the stocks show similar trends, but some show flat behavior.

The 50- and 200-day simple moving average (SMA), and the 12- and 26-day exponential moving averages (EMA), are plotted for Apple's (AAPL) adjusted closing price, as presented in Figure 3. We found that shorter-term averages are more sensitive to changes, compared to longer-term trends for both indicators. The 200-day SMA shows considerable deviation from the actual price movement, while the 50-day SMA generally follows the overall trend. In contrast, both the 12- and 26-day EMAs show close tracking movement against the actual price, but the 26-day EMA shows a slightly late response. This pattern is similarly observed across the price movements of other companies.

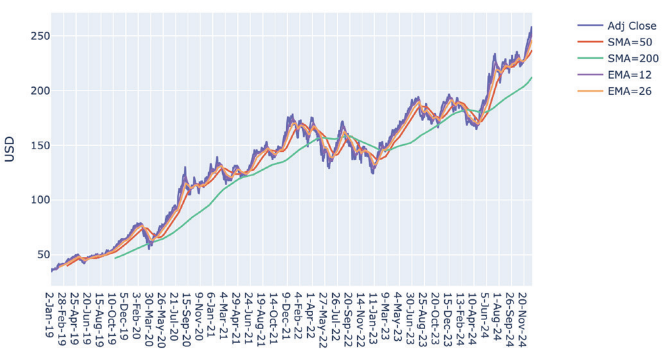

Figure 3: A historical chart of the adjusted close for Apple Inc. (AAPL) during the selected period (from Jan. 2, 2019, to Dec. 30, 2024) with 50- and 200-day simple and 12 and 26-day exponential moving average indicators. Simple and exponential moving averages exhibit upward trends, coinciding with the increase in the adjusted close over the specified time period. However, there is a slight difference between the two moving averages, depending on the calculation method.

The moving average convergence divergence (MACD) and its signal line (MACD-signal) are commonly used to detect trend reversals and to identify potential entry and exit points in the equity market.[15] The range scale defines the MACD is defined by the range scale by subtracting the 26-day EMA from the 12-day EMA, from which a fast-moving line can be obtained. The MACD signal line is a slow-moving line, defined as the 9-day EMA of the MACD line itself. Although the MACD and MACD signal can sometimes be classified as momentum indicators, we treated them as trend indicators in this study. As shown in Figure 4, the signal line moves more smoothly than the MACD line; however, both generally reflect similar strengths in the price movements of AAPL.

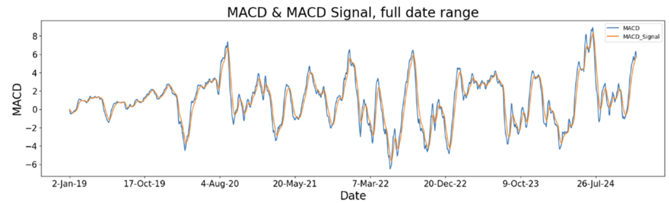

Figure 4: Moving average convergence and divergence (MACD) and MACD-signal indices obtained from the adjusted close of Apple Inc. (AAPL). Both indices exhibit similar strengths in upward and downward movement, but the MACD signal shows a slightly smoother transition. The difference between these two indicators is likely mostly negligible.

As momentum indicators, the relative strength index (RSI) and stochastic oscillator (SO) were applied to measure the magnitude and velocity of change in the adjusted closing price of the stocks. The RSI chart, as shown in Figure 5, measures momentum on a scale of 0 to 100, helping to identify potential trading opportunities. It typically indicates overbought conditions when the value is above 70—suggesting a potential selling opportunity—and oversold conditions when the value is below 30—suggesting a potential buying opportunity.[17] The SO works in a similar way, which implements a scale of 0 to 100 to identify the signals of the possible trading action. It indicates overbought and oversold conditions for above 80 % and below 20 %, respectively. In the SO chart (Figure 6), two indices are shown: %K (STOK) and %D (STOD). %K represents the current adjusted closing value relative to the 14-day range, while %D is a 3-day moving average of %K, resulting in a smoother signal. Figure 6 displays the SO index along with the adjusted close of Apple Inc. (AAPL). Even as AAPL's adjusted close price trends upward over the observed period, the STOK and STOD lines oscillate upward or downward, highlighting potential buying and selling opportunities.

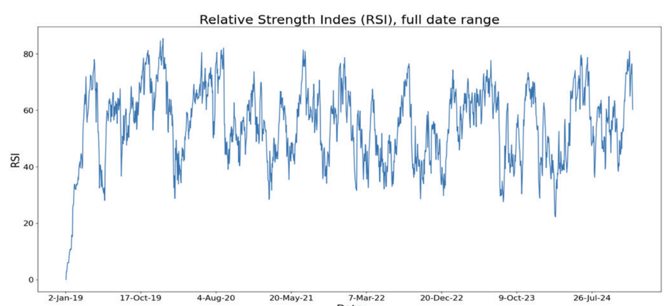

Figure 5: Relative Strength Index (RSI) based on the adjusted close of Apple Inc. (AAPL). The index exhibits both upward and downward movement momentum of the adjusted closing stock price of AAPL. As expected from the mathematical model, the indicator describes the moment of buying and selling trends.

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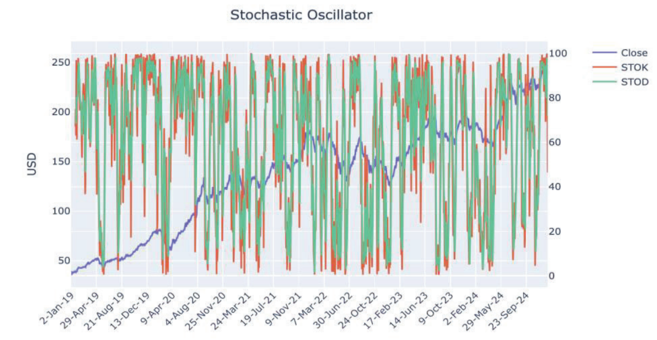

Figure 6: The stochastic oscillator (SO) index, along with the adjusted closing price of Apple Inc. (AAPL), is indicated by STOK and STOD. (%) K presents a 14-day moving average of the closing price, and (%) D indicates a smooth line of K over 3 days. The left y-axis indicates the adjusted closing price, and the right axis indicates the range of 0-100%. The difference between STOK and STOD is hardly noticeable, but it seems that both show very similar trends.

As a volatility indicator, the Bollinger Bands (BB) are plotted against AAPL's adjusted closing price to illustrate price volatility and identify potential trading opportunities, as shown in Figure 7. In this context, volatility refers to the degree of price fluctuations in the stock market and serves as a measure of price stability. The middle line of the BB is the 20-day simple moving average (SMA), while the upper and lower bands are calculated as two standard deviations above and below the SMA, respectively. As shown in Figure 7, the width of the Bollinger Bands expands alongside increases in AAPL's adjusted closing price, reflecting greater volatility.

We were able to build a comprehensive picture of each company's unique stock behavior using this set of technical indicators, as described above. This holistic view was essential for investigating the market relationships at the core of our study. And the individual outcomes were applied for the Johansen co-integration test.

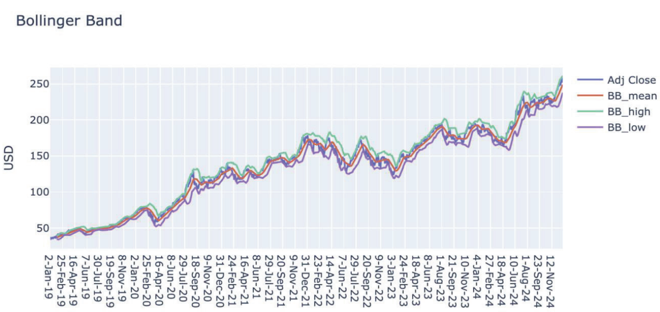

Figure 7: Bollinger band (BB) lines with the adjusted close price of the AAPL chart. BB lines are indicated by three lines: middle (mean), high, and low lines, which are acquired by a 20-day simple moving average (SMA) and two standard deviations for the above or below value. The three individual trends of the BB indicator are moving simultaneously along with the date proceeds, and the different exist, considering the statistical meaning.

Johansen Cointegration:

Before running our main cointegration comparison, we had to pre-process the data obtained from the technical analysis. It is because the companies' stocks are traded in different currencies. We normalized all the values with the mean of the statistics to ensure a fair, apples-to-apples comparison, as shown in Figure 8. As described in Table 2, we paired each of the three major chip-consuming companies with each of the three chip manufacturers in one-on-one comparison. This pairing was effective for assessing the specific influence that chip makers have on the market movement of the companies that use their chips. Finally, the Johansen cointegration test was performed.

In the cointegration test, the first step was to calculate the critical values under the null hypothesis of zero cointegration relationship (r = 0). Then, we sequentially computed the values for $r > 1$ and $r > 2$. Here, "*r*" represents the rank, indicating the number of cointegration vectors under the null hypothesis.[9] The critical values serve as the thresholds for determining whether different non-stationary time series data can be statistically related in a long-run equilibrium.

Next, we calculated the trace statistics for each pair as shown in Table 2, based on Equation 1. This trace statistic value is the number that we can compare against the critical values, which provides a mathematical proof needed to determine how many cointegration relationships (r) exist among variables.[9]

$$Tace\ Statistics = -T \sum_{i=r+1}^{k} \ln(1-\lambda_i) \quad (1)$$

Here, T is the number of observations, K is the number of variables, and λ_i is the i-th eigenvalue from the decomposition.

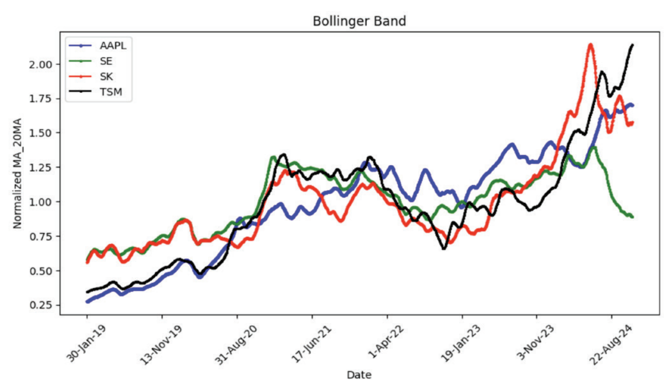

Figure 8: The normalized Bollinger Bands (BB) indices of Apple, Inc. (AAPL), Samsung Electronics (SE), and Taiwan Semiconductor Manufacturing Company Limited (TSM) are based on the indication by STOD (D%). Each curve shows a different behavior, even though they gradually increase along with the progression of the data.

Table 2: The pairs of the chip makers and consumers for the Johansen cointegration test. The A, B, and C in the parentheses define the individual pair. This is the simple combination used for this study, only to compare each big tech company's performance.

Semiconductor / Consumer Big Tech	AAPL (A)	LNVGY (B)	NVDA (C)
Semiconductor Major Manufacturer	SE (A1)	SE (B1)	SE (C1)
	SK (A3)	SK (B2)	SK (C2)
	TSM (A3)	TSM (B3)	TSM (C3)

Results and Discussion

The critical values for the Johansen cointegration test are not derived from a simple analytical formula. Still, they are obtained from simulated distributions corresponding to specific confidence levels, such as 99%, 95%, and 90% (i.e., significance level of 1%, 5%, and 10%, respectively). For our analysis, we used Python's *Statsmodels* library, which provides these simulated values for both the trace and maximum eigenvalue tests in the asymptotic distribution approach.[9,10] We utilized this library to produce the critical values for our specific hypothesis test for r = 0, ≤ 1, and ≤ 2, which are presented in Table 3 for each confidence level. These confidence values were initially acquired during the Johansen cointegration analysis. Each confidence value numerically exhibits the maximum cointegration that can be rejected for the level of the null hypothesis, without considering eigenvalues for the numerical calculation of the cointegration. Namely, these are used as the minimum values for cointegration for each pair.

Table 3: The critical values for the cointegration confidence level and the null hypothesis rank (*r*). The numbers indicate the minimum values for each category, specifically the values required for confidence optimization. The values decrease as the confidence level increases.

Confidence Level	Column 1 (r =0)	Column 2 (r <= 1)	Column 3 (r <= 2)
90%	44.49	47.85	54.68
95%	27.07	29.80	35.46
99%	13.43	15.49	19.93

The trace statistics were also calculated for each pair in Table 2 with the cointegration rank via Python's Statsmodels package. If the trace statistic exceeds the critical value at a given rank (*r*)—that is, if *trace statistic* > *critical value*—the current null hypothesis can be rejected, and the test proceeds to the next rank. For example, in the case of $r = 0$ in Column 1, if the trace statistic exceeds 44.49 at a 90% confidence level, the null hypothesis of no cointegration is rejected, and we move on to test for $r < 1$. This implies that there may be at most one cointegration relationship, indicating that the variable—such as a stock indicator—exhibits more than zero cointegration relationship between the chip makers and consumers. We applied this procedure to all pairs listed in Table 2 and present the resulting trace statistics in Table 4. To make the table easy to read, we color-coded the results: A green background in the table indicates no cointegration relationship. In contrast, an orange background indicates the presence of at least one cointegration between the variables. The values in Table 4 present the trace statistics from the Johansen cointegration test for each pair of stock indicators in Table 2. Since the eigenvalues (specific scalar approach) are not considered in this study, the trace statistic from the cointegration test is used to determine whether the null hypothesis is rejected at each confidence level. Therefore, the trace statistics are important for examining the cointegration. As marked with a colored background in each cell, the moving indicators show no integration, while the momentum indicators exhibit strong cointegration.

We also created a 3D plot showing the trace statistics values for each pair alongside their corresponding stock indicators, which makes it easy to identify the high trace statistic values. The high values are prominent because they indicate the presence of at least one cointegration relationship between the indicator variables.

The results of our study suggest that during periods of broad economic instability, the stock trends of semiconductor manufacturers and the major technology companies that consume their chips may become closely aligned. At this time, tech companies manage their production to minimize losses, so that this decision directly impacts chip demand. This tendency is likely to become predominant with a dynamic intensified by the recent turmoil from the COVID-19 pandemic and rising trade protectionism. As addressed in the literature,[11,12] although the business model has not been well developed for full capturing of the volatility dynamics of the financial and economic cycle, empirical and existing theories have shown the stock's sensitivity and co-movement to economic fluctuation across various economies.[18]

For trend analysis across multiple variables, time-relevant features need to be considered to improve analysis performance. However, in this study, we only examined the defined cointegration among commercial market equities over a specific time period. This may be why our results show a distinct difference between momentum and trend indicators. We suggest that time-series analysis should be advanced in correlation or cointegration analysis, or that such analysis be performed for stronger quantitative evaluation. This will be proposed for our next project. In addition, our model does not reflect intangible macroeconomic parameters such as interest rates and the Korean won-to-US dollar exchange rate; as a result, the cointegration results likely further demonstrate the impact of these unobserved features rather than pure firm-level interactions. Indeed, a small sampling (only six companies: three semiconductor manufacturers and three semiconductor consumers) would limit the confidence in the more relevant analysis.

For the time-series analysis, our technical approach did not include trajectory evaluation in a time period, which is typically used to determine whether the trend is stationary or non-stationary. The fact of this evaluation is beneficial for systematically estimating the relation between the trends of two variables over time. This evaluation will be able to effectively discriminate between a pair of companies with similar trend fluctuations among multiple companies. In addition, asymmetric market analysis was not included in our study, so our results may not apply to other specific time periods or semiconductor economic cycles. Such analysis is called volatility-spillover analysis. We will also include these techniques for future analysis and believe that this proposed approach will provide further details on the correlation and cointegration analysis.

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Table 4: The trace statistic values from the Johansen cointegration test for each pair of stock indicators are presented in Table 2. The moving indicators show no integration, while the momentum indicators exhibit strong cointegration.

Big Tech	Manufacturer	50SMA	12EMA	MACD_Signal	RSI	SO	BB
APPL	SE	25.68	17.40	207.14	104.57	179.19	22.66
	SK	7.74	7.59	176.82	86.90	159.11	6.37
	TSM	5.86	4.59	126.81	73.99	151.08	5.25
LNVGY	SE	26.91	24.79	213.59	114.63	164.52	24.40
	SK	12.04	13.42	179.91	84.82	158.71	10.36
	TSM	7.28	5.45	142.12	76.46	149.48	8.77
NVDA	SE	37.89	29.31	218.40	104.77	171.02	37.32
	SK	23.63	16.74	199.66	82.88	158.53	23.53
	TSM	6.18	7.02	90.49	75.86	151.30	4.67

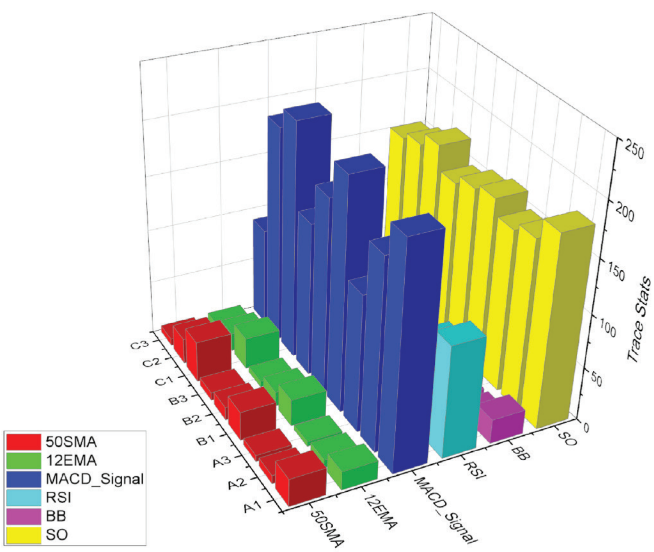

Figure 9: 3D plot of the trace statistics for each pair in Table 2 from the Johansen cointegration test. This plot provides an easy-to-read representation of the level of cointegration in terms of the trace statistics.

Conclusion

In this study, we evaluated chip makers' performance by leveraging the stock trends of their key consumers. Based on the technical analysis, we applied the Johansen cointegration test to assess the relationships between these groups quantitatively. Although the data selection is limited to only six companies in total, our technical approach highlights the distinct interdependencies in the semiconductor economy. The finding can be beneficial for understanding the market dynamics and the complex nature of global trade and supply chain instability in the short term.

It is observed that momentum indicators—such as the Relative Strength Index (RSI) and Stochastic Oscillator (SO)—are most effective at revealing the strong relationship between chipmakers and consumers. Different from the trend indicators or volatility indicators, the moment indicator shows a close relationship by measuring the speed of price changes. However, the MACD indicator is an interesting exception. Even though we classified the MACD as a trend indicator, it did show a solid connection. It would be because its formula is based on the incorporation of the elements of both trend and momentum. Likely, the MACD seems to capture not only the market direction but also the strength of price movements.

Based on our findings, the indicators that measure price momentum (strength and speed) are more suitable for analyzing the semiconductor market, compared to the indicators that track general trends or price fluctuations. In addition, the critical cointegration cannot be considered for the movement of the trends in the long-term direction. Still, it will be more prominent when reacting to market pressures with similar force and speed in short-term volatile times. However, in our technical analysis, the asymmetric market evaluation, volatility-spillover study, and correlation related to stationary or non-stationary movement are not included due to technical complexity. Such analysis would be beneficial for further effective discrimination of the individual markets pairing and performance evaluation, regarding macroeconomic parameters. Nevertheless, we believe that our findings can help investors and economic analysts make more informed decisions by highlighting the strong underlying connection between technology and semiconductor firms, especially in rapidly changing markets.

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