The Impact of Digitalization and Artificial Intelligence in Finance. How Artificial Intelligence Replaces Quantitative Analysis

Theo-Dorian BUFTEA
Investment and Development Bank, Bucharest, Romania

Ioana VĂDUVA- SIMA
Ministry of Finances, Bucharest, Romania

Cristina TUȚU
Emergency Clinical Hospital Bagdasar Arseni, Bucharest, Romania

Adrian Pavel VULCU[*]
Therme PEN, Bucharest, Romania
[*]Corresponding author, vaduvasima@yahoo.com

Abstract. *The study highlights the investment efficiency in a single listed stock in the field of artificial intelligence, specifically in Advanced Semiconductors Materials Lithography. A series of scientific papers have been reviewed in the analyzed field that highlight this aspect. The research is based on the development of a trading program starting from the stock price of Advanced Semiconductor Materials Lithography versus the company's stock price/sales (as a fundamental indicator). The goal is to identify trading opportunities based on trends given by the moving averages (50 days and 200 days of the analyzed company) used to identify trends. Independently, a program has been developed that considers the positioning of trading orders based on the 5-year stock price difference between Advanced Semiconductor Materials Lithography and a reference index - namely an Exchange Traded Fund called Vaneck Semiconductor - using a correlation index of 0.7 (an index considered in most studies), tracking the divergence between the two aforementioned stocks, using the principle of 'mean reversion'. It is noted that the data used for the analysis were sourced from the Bloomberg platform. Considering the fundamental evolution of the company and the industry in which it operates, as well as the results of the two programs, we believe that Advanced Semiconductors Materials Lithography has good growth prospects*
The scope of the study is to demonstrate the importance of the company in the evolution and development of generative AI through its unique products.

Keywords: digitalization, artificial intelligence (AI), finance, trading, financial markets.

Introduction

In the context where digitalization and artificial intelligence are increasingly present in many fields, we consider that the research aims to highlight the advantages of algorithmic trading. Moreover, today, in trading activities both in the capital market and in other financial markets, standardized and non-standardized instruments are used. The increasing competition in the AI field represents a positive element in the race to develop Large Language Models (LLM).

As technology companies evolved, the level of investment spending allocated to the development of artificial intelligence has increased significantly, with each entity trying to find more efficient models. In this context, efficiency benefits both traders and investors, contributing to a transparent and competitive financial ecosystem. Furthermore, the entire financial system is affected by the changes imposed on financial markets, and AI will amplify the inherent

DOI: 10.2478/picbe-2025-0220

procyclicality of the financial system beyond what the current decision-making process does (Daníelsson et al., 2022).

Since the funds allocated on the development of generative artificial intelligence are increasing almost every month, ASML has allocated resources for the research and development area. Algorithmic trading reduces the emotional impact on traders, ensuring efficient execution of transactions. Additionally, the study of the capital market from the perspective of behavioral finance, analyzing the rational vs. non-rational approach in trading, will play an important role (Obreja-Brașoveanu et al., 2011).

The practical consequence arises from how the financial system is affected by the changes brought by the accelerated developments in the field of generative artificial intelligence. The rapid development of fintech has played an important role in the digital transformation of enterprises, and the number of alternative data and rapidly evolving machine learning models have become key factors in promoting innovation in financial technology in recent years. However, these advanced technologies for improving financial life will also bring a series of new risks (Cao, Zhai, 2022).

The purpose of the study is to show that, based on its unique product, the company represents an important step forward in achieving its vision, in other words "to enable groundbreaking technology to solve some humanity toughest challenges", as stated by the company itself. Moreover, the uniqueness of its products offered by the company represent an important contribution to the development of its financial tools such as a thorough analysis of financial trends or complex financial solving issues, replacing quantitative analysts

Literature review

According to the authors (Briest et al., 2023), digitalization and generative artificial intelligence represent an important step for the world of finance. The ability to learn from a large volume of unstructured data plays an important role in activities such as customer support services (e.g., 'call centers'), fraud prevention, risk management, or coding activities. However, the use of generative artificial intelligence in sensitive activities such as decision-making or determining investment strategies for clients requires a lengthy process.

Goodell (2021) highlights that the financial services industry increasingly relies on new, modern methods supported by hardware and software advances that allow machines to develop large, complex models that lead to robust evaluation of new information. In particular, the adoption of artificial intelligence (AI) and machine learning (ML) is radically transforming trading and investment decisions. Concurrently, research in financial theory and practice responds to the need to better understand the utility and economic impact of artificial intelligence (AI) and machine learning (ML).

The study by the authors (Dixon et al., 2020) presents the two related technologies that are emerging in financial research, artificial intelligence (AI) and machine learning (ML). The authors present a series of examples used in trading, stochastic volatility, and fixed income modelling. They also present the effects on trading in financial markets, investments, and wealth management.

Another author (Aldridge, 2013) reviews high-frequency trading (HFT) and highlights the benefits resulting from it for the harmonious development of markets, through price transparency and reduced trading costs.

According to (Cartea & Jaimungal, 2013), the market has changed in recent years, where most transactions are designed and executed by computerized algorithms, so the increasing presence of artificial intelligence (AI) has changed not only the speed at which transactions occur, but also other fundamental characteristics related to influencing stock prices.

Jansen (2020) mentions in one of his works that an explosive growth of digital data has stimulated the demand for expertise in trading strategies that use machine learning (ML). The author illustrates this using example ranging from linear models and tree-based ensembles to advanced learning techniques from cutting-edge research.

On the other hand, (Hilpisch, 2020) highlights that 'the moment these technologies are combined with the programmatic availability of historical and real-time financial data, the finance area will fundamentally change.' The author shows that practical ways to apply machine learning algorithms will have a lasting impact on financial theory and practice and help correct statistical inefficiencies in financial markets.

Research conducted by (Scarpino, 2019) emphasizes that data-driven finance, artificial intelligence (AI), and machine learning will have a lasting impact on financial theory and practice. Identifying and exploiting economic inefficiencies through algorithmic trading - the automatic execution of trading strategies in financial markets will influence the competitive dynamics in the financial area and could potentially bring about the emergence of a financial singularity.

In Narang's (2013) study, the author provides information about high-frequency trading and explains in non-mathematical terms what quantitative and algorithmic trading are and how they work.

However, we must consider that in the context of money management, emotions seem to dominate objective logic. Thus, the appetite for investment risk increases at the most inappropriate time, precisely when the capacity to take on additional risk is decreasing due to the decline in the market value of the portfolio (Obreja-Brașoveanu et al., 2011).

According to the author (Lee, 2020), artificial intelligence (AI) can lead to systemic risks and market manipulation on trading platforms. Additionally, the author makes policy recommendations and suggests some directions for the use of AI in financial services to improve access to finance. Some authors (Al-Sartawi et al., 2022) have concluded based on their analyses that 'the financial sector plays an essential role in this challenge posed by the application of digitalization and artificial intelligence; therefore, it is important to finance the necessary investments and technologies to transform the global economy into a sustainable one'.

Aside of the important usage of generative artificial intelligence in a field like medicine, the development of large language models will have a solid impact in the financial area, such as automatization of financial analysis by using previous experiences of different analysts with a high expertise in the above-mentioned industry.

Methodology and Data

The purpose of using Advanced Semiconductors Material Lithography as an example is to emphasize the uniqueness business model, in terms of product offering. Therefore, we consider that the above-mentioned company represents a good investment alternative.

We want to emphasize that - by analysing the company - we can therefore draw the conclusion that the price is often overvalued but, in reality, due to its position within the market, the company is a good investment opportunity.

The database used in the research consists of data collected from Bloomberg. As a methodology, a trading program was used to highlight market signals, and based on a trading program, a potential trading decision was applied relative to a 'proxy' correlated with the industry in which ASML operates, namely the 'VANECK SEMICONDUCTOR ETF' (SMH). The authors developed the trading program in the Python programming language, using Jupyter Notebook.

Using that above-mentioned Exchange Traded Fund, as we will mention below, the investments that are part of the investment covers competitors and companies specialized in the chip production area.

An 'Exchange-Traded Fund' represents an investment fund that holds multiple underlying assets and can be bought or sold on a regulated market like a listed stock. The aforementioned ETF is registered in the USA, tracking the performance of the largest semiconductor manufacturers in the USA. The total assets under management amount to 23.120 billion USD, and it was initiated in 2011. The performance of the index is shown in Figure 1.

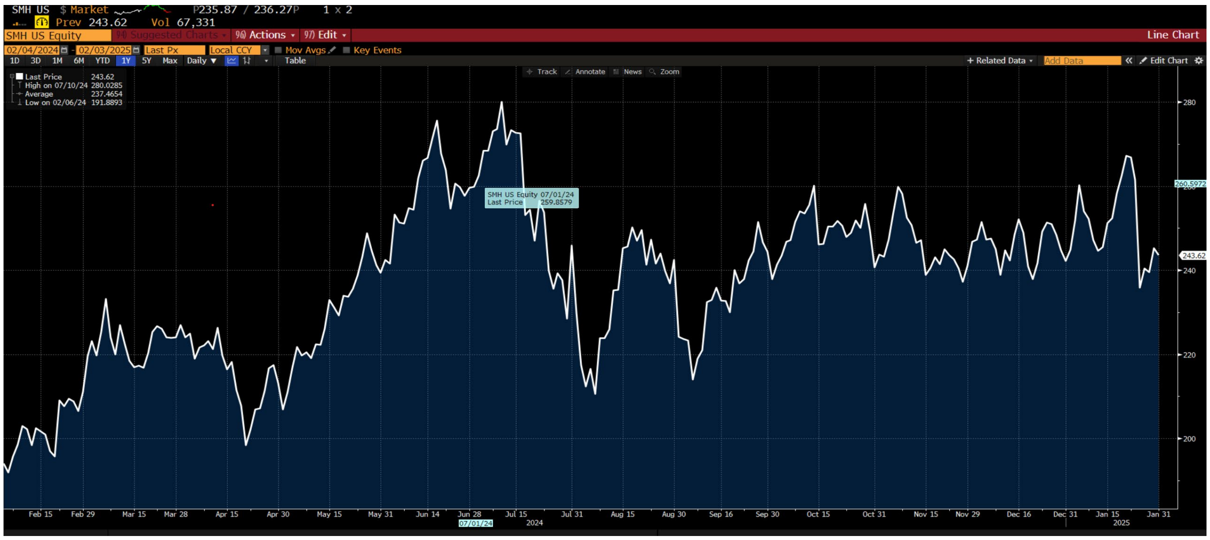

Figure 1. Price evolution of the ETF „VANECK SEMICONDUCTOR"

Source: data collected from Bloomberg platform.

The ETF in question has its main holdings structure in the following companies (top 10).

Table 1. Structura ETF „Vaneck Semiconductor" on 5th of February 2025

Company name	Holding as percentage in the fund	Market value (mil. EUR)
NVIDIA Corp	17.91%	4,300.00
Taiwan Semiconductor Manufact	12.98%	2,930.00
Broadcom	9.28%	2,060.00
ASML	5.16%	1,200.00
Qualcomm	4.84%	1,120.00
Applied Materials	4.78%	1,070.00
Advanced Micro Devices - AMDD	4.57%	1,050.00
Texas Instruments	4.35%	983.35
LAM Research	4.11%	909.53
Analog Services Inc	3.96%	983.00

Sursa: data collected from Bloomberg platform.

The main financial indicators of the ETF are:

- Average dividend yield: 0.90%
- Average Price/Book ratio: 5.77
- Average Price/Earnings ratio: 73.12

The program considers the positioning of buy/sell orders based on the 5-year stock price difference between ASML and SMH. It is noted that the data used for the analysis were sourced from the Bloomberg platform. Additionally, the authors developed a trading program starting from the stock price of Advanced Semiconductors Materials Lithography versus the 'price-to-sales' of the same company. The results can be seen in the appendix no.1.:

Results and Discussions

Some initial comments related to the two trading programs:

- Regarding the correlation model of 'ASML' vs. the 'SMH' ETF, an overvaluation of ASML stock is noticed. This can be explained by the fact that the analyzed ETF also includes companies that produce older generation chips, which do not require such complex lithography machines.
- We used the 'mean reversion' strategy in the comparative analysis between ASML and SMH. Practically, we assumed that the ASML stock price would converge towards the SMH ETF in a five-year analysis. It is noteworthy that following the beginning of 2024 that gave a final sell signal, even though the stock price increased compared to the ETF, there were no further signals of this kind. This shows us that the potential of the index has a future growth dynamic closer to the ASML price level.
- Regarding the analysis of ASML versus the evolution of the 'Price-to-Sales' indicator, a buy level appears in 2015 followed by several sell levels in the following years (marked with a red arrow). However, historically speaking, the price-to-sales ratio analysed at the company level (Figure 2) shows that it is below the average of the last five years.

Figure 2. The evolution of the Stock Price/Sales in the period March 2020 - February 2025

Source: data collected from Bloomberg platform Comment: The figure below is a representation of data existing within Bloomberg application, while the image was snipped from the same application.

Conclusion

Based on the above, the company presents interesting investment prospects considering the following factors:

- The demand for marketed products is high due to the increasing demand for products related to the production of artificial intelligence software and the growing competition in the field.

- The company provides customers with everything they need to mass produce patterns on sillicon allowing them to increase the value and lower the cost of a chip;
- It is the only company that produces systems for manufacturing of advanced logic and memory chips including 3 nm nodes
- Gross profit margin of over 50%.
- High investor interest, being a 'hot' industry.
- An economic enabler, providing the main source of hardware for artificial intelligence creators, which will lead to increased global productivity.
- Professional management with high competencies.
- Sales distribution across multiple continents, resulting in high revenue granularity.
- Analysts' forecasts indicating growth potential based on future revenues.
-

However, there are some disadvantages:

- The company has sales restrictions imposed by the Dutch government regarding the Chinese market, a rapidly developing market, which limits its sales scope.
- There are some competitors such as Taiwan Semiconductors or Applied Materials and we expect them to become active within the industry
- Compared to the indices considered as proxies (see the comparative analysis above with the 'SMH' ETF), the stock price seems relatively expensive.

Due to its uniqueness within the chip production industry and its relative low valuation, we consider the company as being an attractive value investment proposition.
Since the evolution of Large Language Models are at their infancy, we consider ASML as a valuable asset in the further development of the generative artificial intelligence.
As a future endeavor, we consider this study as a good starting point in further development of artificial intelligence in the domain of finance. The development of new products and features will be beneficial in the financial analysis of different companies by standardizing the approach done by professionals.

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Appendix no 1.

```
# Compute moving averages for trend detection
df['ASML_50MA'] = df['ASML Price'].rolling(window=50).mean()
df['ASML_200MA'] = df['ASML Price'].rolling(window=200).mean()
# Compute z-score for mean reversion strategy
def zscore(series):
    return (series - series.mean()) / series.std()
df['P/S_Zscore'] = zscore(df['ASML Price to Sales'])
# Compute rolling correlation between ASML and SMH
df['ASML_SMH_Corr'] = df['ASML Price'].rolling(window=50).corr(df['SMH Price'])
# Define trading signals based on correlation
corr_conditions = [
    (df['ASML_SMH_Corr'] > 0.7) & (df['ASML Price'] > df['SMH Price']),  # ASML is overperforming SMH,
potential mean reversion
    (df['ASML_SMH_Corr'] > 0.7) & (df['ASML Price'] < df['SMH Price'])   # ASML is underperforming SMH,
potential mean reversion]
corr_choices = [-1, 1]  # -1 for Short ASML, 1 for Long ASML
df['Corr_Signal'] = np.select(corr_conditions, corr_choices, default=0)
# Define trading signals based on P/S Z-Score
ps_conditions = [
    (df['ASML Price'] > df['ASML_50MA']) & (df['ASML_50MA'] > df['ASML_200MA']) & (df['P/S_Zscore'] < 1),
# Bullish trend, undervalued
    (df['ASML Price'] < df['ASML_50MA']) & (df['ASML_50MA'] < df['ASML_200MA']) & (df['P/S_Zscore'] > 1)
# Bearish trend, overvalued]
ps_choices = [1, -1]  # 1 for Buy, -1 for Sell
df['PS_Signal'] = np.select(ps_conditions, ps_choices, default=0)
# Compute strategy returns separately for both models
df['Daily Return'] = df['ASML Price'].pct_change()
df['Corr_Strategy Return'] = df['Corr_Signal'].shift(1) * df['Daily Return']
df['PS_Strategy Return'] = df['PS_Signal'].shift(1) * df['Daily Return']
df['Corr_Cumulative Return'] = (1 + df['Corr_Strategy Return']).cumprod()
df['PS_Cumulative Return'] = (1 + df['PS_Strategy Return']).cumprod()
# Plot ASML and SMH prices
plt.figure(figsize=(12,6))
plt.plot(df.index, df['ASML Price'], label='ASML Price', color='blue')
plt.plot(df.index, df['SMH Price'], label='SMH Price', color='purple')
plt.legend()
plt.title('ASML & SMH Prices')
plt.show()
# Plot P/S ratio
plt.figure(figsize=(12,6))
plt.plot(df.index, df['ASML Price to Sales'], label='P/S Ratio', color='orange')
plt.legend()
plt.title('ASML Price-to-Sales Ratio')
plt.show()
# Plot correlation
plt.figure(figsize=(12,6))
plt.plot(df.index, df['ASML_SMH_Corr'], label='ASML-SMH Correlation', color='green')
plt.legend()
plt.title('ASML-SMH Rolling Correlation')
plt.show()
# Plot Z-score
plt.figure(figsize=(12,6))
plt.plot(df.index, df['P/S_Zscore'], label='P/S Z-Score', color='red', linestyle='dashed')
```

```
plt.legend()
plt.title('ASML P/S Z-Score')
plt.show()
# Plot correlation model signals
plt.figure(figsize=(12,6))
plt.plot(df.index, df['ASML Price'], label='ASML Price', color='blue')
plt.scatter(df.index[df['Corr_Signal'] > 0], df['ASML Price'][df['Corr_Signal'] > 0], marker='^', color='green',
label='Buy Signal')
plt.scatter(df.index[df['Corr_Signal'] < 0], df['ASML Price'][df['Corr_Signal'] < 0], marker='v', color='red',
label='Sell Signal')
plt.legend()
plt.title('ASML Trading Signals - Correlation Model')
plt.show()
# Plot P/S model signals
plt.figure(figsize=(12,6))
plt.plot(df.index, df['ASML Price'], label='ASML Price', color='blue')
plt.scatter(df.index[df['PS_Signal'] > 0], df['ASML Price'][df['PS_Signal'] > 0], marker='^', color='green', label='Buy
Signal')
plt.scatter(df.index[df['PS_Signal'] < 0], df['ASML Price'][df['PS_Signal'] < 0], marker='v', color='red', label='Sell
Signal')
plt.legend()
plt.title('ASML Trading Signals - P/S Z-Score Model')
plt.show()
# Plot cumulative returns for correlation model
plt.figure(figsize=(12,6))
plt.plot(df.index, df['Corr_Cumulative Return'], label='Correlation Model Cumulative Return', color='purple')
plt.legend()
plt.title('Strategy Performance - Correlation Model')
plt.show()
# Plot cumulative returns for P/S model
plt.figure(figsize=(12,6))
plt.plot(df.index, df['PS_Cumulative Return'], label='P/S Model Cumulative Return', color='orange')
plt.legend()
plt.title('Strategy Performance - P/S Z-Score Model')
plt.show()
## Strategy description
#The trading model is divided into two independent strategies:
#Correlation-Based Strategy
  #This strategy analyzes the rolling correlation between ASML and the SMH index (semiconductor ETF).
  #When ASML significantly outperforms SMH in a high-correlation regime, the model generates a Sell signal
(expecting mean reversion).
  #When ASML underperforms SMH, a Buy signal is generated.
#P/S Z-Score Strategy
  #This model uses the Price-to-Sales (P/S) ratio to assess relative valuation.
  #A Buy signal is triggered when ASML is in a bullish trend (above moving averages) and has a low P/S Z-Score.
  #A Sell signal is triggered in a bearish trend with an overvalued P/S Z-Score.
#Performance Tracking
  #Each strategy's trading signals are plotted separately for evaluation.
  #The model aims to capture both relative value opportunities and fundamental mispricing’s in ASML.
```

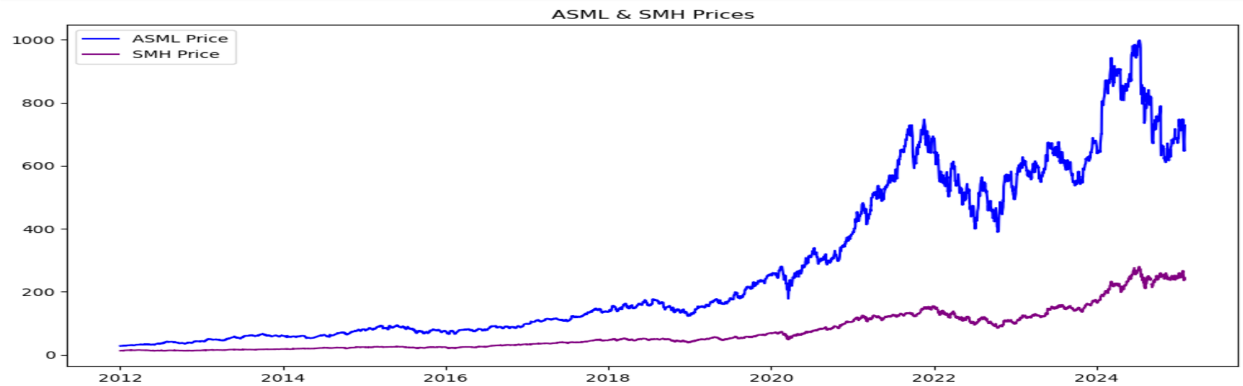

Figure 1. The evolution of the stock price of 'ASML' vs. 'VANECK Semiconductors' ETF in the period 2012-2024

Source: Processing in Python Notebook based on data collected from Bloomberg.

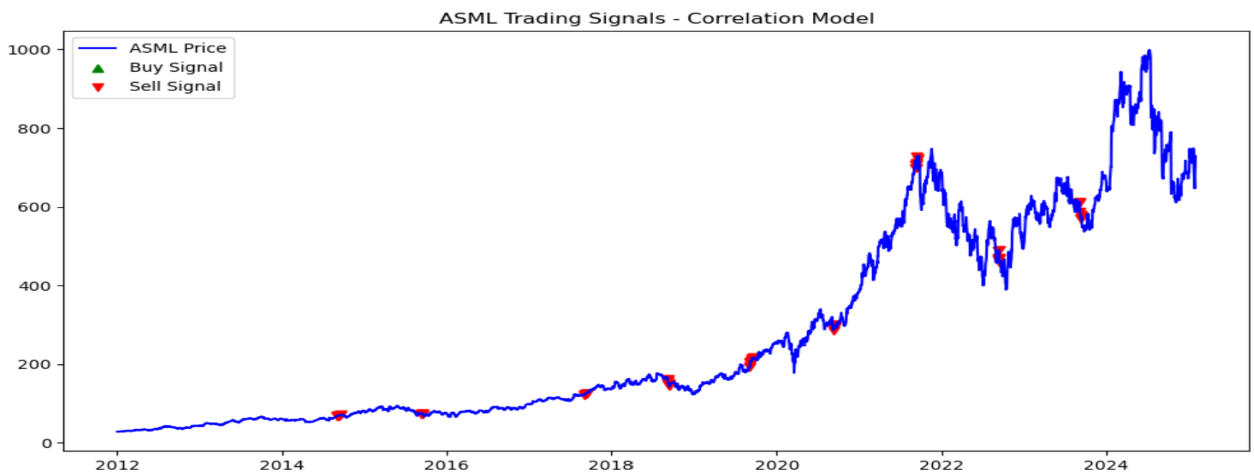

Figure 2. Correlation model ASML vs. VANECK and the buy/sell signals of ASML

Source: Processing in Python Notebook based on data collected from Bloomberg.

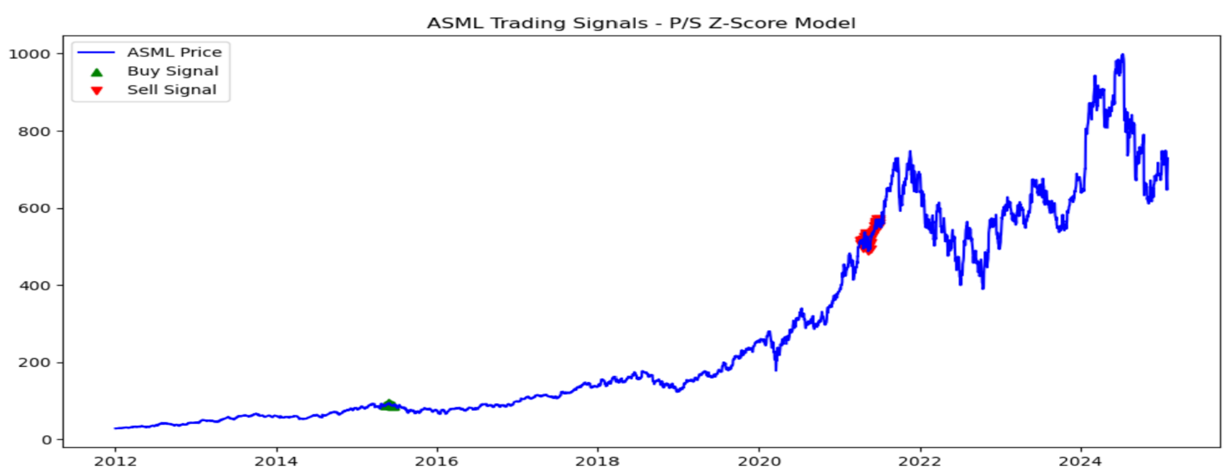

Figure 3. Trading signals of ASML vs. the evolution of Price-to-Sales using Z-Score (indicator value – mean/1 standard deviation)

Source: Processing in Python Notebook based on data collected from Bloomberg.