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Efficiency Market Hypothesis within the Semiconductor Industry

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Abstract:

This study examines the market efficiency of the semiconductor industry using the VanEck Semiconductor UCITS ETF (SMGB.L) and its constituent stocks as proxies. Using the Rescaled Range (R/S) methodology, the research aims to understand the fractal properties and long-term dependencies in the semiconductor market as captured by the Hurst exponent. The R/S methodology is critical in identifying patterns of persistence or mean reversion, providing insight into whether the price movements of these assets are consistent with the Efficient Market Hypothesis (EMH). Our analysis covers daily adjusted closing prices from December 2020 to June 2024 for the ETF and its 25 constituents. The results reveal divergent behaviour: while some stocks exhibit random walk characteristics, suggesting market efficiency, others show significant mean-reverting tendencies, suggesting deviations from the EMH. Rolling window analysis further reveals the temporal evolution of these behaviours, highlighting periods of both efficiency and inefficiency in response to changing market conditions. Notably, major stocks such as NVIDIA, ASML and AMD closely follow the EMH, while others such as Texas Instruments and Microchip Technology exhibit mean-reverting patterns. This study highlights the complexity of market dynamics within the semiconductor sector and provides valuable insights into its fractal characteristics. The application of the R/S methodology in this context is particularly significant, as it not only assesses market efficiency, but also helps investors and analysts understand the predictability of stock returns in this rapidly evolving industry. Future research could extend these findings by exploring multifractal behaviour and integrating advanced machine learning models to improve predictive capabilities in financial markets.

Key Words: Semiconductor Industry, Efficient Market Hypothesis (EMH), VanEck Semiconductor UCITS ETF, Fractal Analysis, Hurst Exponent, R/S Methodology, Market Efficiency, Mean-Reversion, Rolling Window Analysis, Stock Returns.

Table of Contents

Table of Figures

Table of Tables

1. Introduction

1.1. Semiconductor Industry and Efficient Market Hypothesis rationale

The semiconductor industry is experiencing exponential growth due to its increasing involvement in society and its critical role in future developments. This growth is being driven by many factors, including the Social Development Agenda for 2030, which emphasises climate action (, 2023), the trend towards digitalisation, and advances in telecommunications and infrastructure.

Since late 2020, the semiconductor industry has faced unprecedented challenges due to a global chip shortage (Zhang & Zhu, 2023). This shortage has highlighted the complex interdependencies within global supply chains (Mohammad et al., 2022). The situation was initially caused by the COVID-19 pandemic and has been further intensified by increased demand for electronic devices, changes in consumption patterns, and the rapid acceleration of digital transformation across various sectors (Voas et al., 2021).

The semiconductor industry's crucial role in technological advancement and innovation has been highlighted by a combination of factors. This has led to a revaluation of strategies to strengthen supply chains, diversify production sources, and increase international cooperation to reduce the risk of future disruptions. Consequently, the semiconductor sector faces significant challenges and opportunities in this landscape (Ramani et al., 2022). To ensure the industry's resilience and adaptability to dynamic demands, it is necessary to revaluate production strategies, invest in advanced manufacturing technologies, and develop innovative solutions (Zhang & Zhu, 2023).

In this study, we will conduct a comprehensive analysis of the characteristic and the returns of both the VanEck Semiconductor UCITS ETF and the individual stocks within it to serve as a proxy for the semiconductor industry. This ETF has only been trading since December 2020, which is a relatively short time series, but as Kirichenko et al. (2020) show in their HITS study, even short time series can provide valuable insights.

Through this analysis, we aim to assess whether the semiconductor industry, as represented by the ETF and its components, aligns with the Efficient Market Hypothesis . According to the Efficient Market Hypothesis , if the market is efficient, prices will be unpredictable and subject to random fluctuations based solely on the available information (Fama, 1970, 1991). This hypothesis suggests that asset prices fully reflect all available information, making it challenging to consistently outperform the market through stock timing or selection (Fama, 1970, 1991; Malkiel, 1989).

1.1.1. Motivation of the study

The motivation for this study lies in the semiconductor industry's crucial contribution to scientific and economic progress (Adams et al., 2013). It is instrumental in the advancement of a diverse array of contemporary technologies, such as sophisticated computational systems and consumer electronics (SIA, 2023). It is essential to comprehend the market efficiency in this industry due to its cyclical and volatile nature, which is influenced by fluctuating demand, rapid technological advancements, and global supply chain modifications (Pan et al., 2024). This analysis holds great importance for portfolio managers and investors who seek to invest in the sector's growth potential and enhance their risk management strategies, specifically in relation to semiconductor equities as the market's efficiency is a crucial factor, as it enables industry growth and ensures proper of capital allocation. Additionally, assessing the Efficient Market Hypothesis in this scenario offers policymakers, regulators, financial institutions and investors valuable insights into the influence of regulatory actions and information dissemination on the evaluation of stock value in a strategically significant industry (Jennings & Barry, 1983). Given that the semiconductor industry has been rapidly evolving in recent years, this analysis can also establish patterns of similarity with other semiconductor-related or even semiconductor-dependent industries that have also had recent buoyant episodes and may suffer from potential inefficiencies as analysed by Wu (2024).

1.2. Objective and Methodology of the Study

The objective of this work is to determine the efficiency of the market industry according to the Efficient Market Hypothesis (Fama, 1970, 1991) in the semiconductor industry by analysing the returns of the ETF "VanEck Semiconductor UCITS " and its proxy components.

For this purpose, a comprehensive analysis of the ETF and its components will be carried out and then, to determine its efficiency, an analysis will be carried out using fractal methodology with the Hurst coefficient. The fractal methodology which going to be used is the R/S methodology in combination with Rolling window analysis and Gaussian white noise creation for the Intervals of confidence.

1.3. Structure of the Study

The Introduction presents a comprehensive explanation of the semiconductor industry's importance and states the study's goal of analysing market efficiency. The article establishes the background by examining the expansion of the sector, developments in technology, and the justification for utilising the VanEck Semiconductor UCITS ETF as a representative of the market.

The Semiconductor Industry Overview examines the distinctive features, major participants, and market prospects of the industry. This chapter explores the various uses of semiconductors, ranging from computing to automotive technology. It also provides detailed information about important firms in the field, which is crucial for comprehending the ensuing analysis.

The EMH chapter introduces the fractal methodology, which serves as the analytical basis for this investigation. This text elucidates the utilisation of fractal analysis and the Hurst exponent to assess market efficiency. This chapter additionally examines prior research that has utilised fractal techniques in different markets, placing the topic within a wider academic discussion.

The primary examination is outlined in the chapters on Data Collection and Preparation and Analysis and Results. This study outlines the methodology used to gather and process data pertaining to the ETF and its individual components for the purpose of analysis. Subsequently, the study provides its findings by employing the Hurst exponent to evaluate whether these assets adhere to the random walk behaviour proposed by the Efficient Market Hypothesis . The study finishes by providing a concise summary of the observations about the market efficiency of the semiconductor business and emphasising the consequences for investors and regulators.

2. Semiconductor Industry

2.1. Definition and characteristics of semiconductors

A semiconductor is a material whose conductivity falls between that of a conductor and an insulator, allowing it to act as either depending on certain conditions such as the presence of impurities, the application of external electric fields, temperature, and light exposure (Singh, 2003). Semiconductors are a fundamental component of diodes, transistors, and integrated circuits. Semiconductors have a dual operation capability, which makes them extremely valuable components for precise control over the flow of electricity in various electronic devices, including computers and smartphones (Siu, 2022; Yu & Cardona, 1997). Semiconductors are inherently pure; however, they can be doped by introducing impurities.

According to Yu & Cardona (1997), when the material is in its pure form, free from impurities and at low temperatures, it is more likely to demonstrate insulating qualities rather than low conductivity. Yu & Cardona (1997) attribute the absence of electrical conductivity in the material to the inadequate energy of the electrons to transition from the valence band to the conduction band, leading to a scarcity of free charge carriers.

When impurities are added, the conductivity increases. According to Cohen et al. (1988), depending on the type of impurity added, the semiconductor becomes either n-type, having an excess electron, or p-type, meaning an excess of holes or positive charge carriers. In addition, as Bube (1992) and Brillson (1982) expose, increasing the temperature can also increase the conductivity of a semiconductor by providing the energy for more electrons to jump from the valence band to the conduction band, where they are free to conduct electricity.

2.2. Primary applications of semiconductors

In the report published by McKinsey & Co, Burkacky et al. (2022) explore the crucial role of semiconductors in powering various technologies that shape our modern digital world. They emphasise the importance of semiconductors in the functioning of common devices like smartphones, computers, and medical equipment. Additionally, the report highlights the significant role of semiconductors in the automotive industry, particularly in the advancement of electric and autonomous vehicles. Moreover, the research explains how the semiconductor sector supports the development of the Internet of Things (IoT), which in turn improves everyday life by increasing ease and efficiency through the use of smarter, interconnected devices. According to the authors, the semiconductor industry is actively seeking strategic innovation and intensifying its research and development endeavours in order to adapt to the growing digital and intelligent society. Lastly, the research also exposes how these efforts are vital for the continuous evolution of semiconductor technologies and their ability to keep up with the rapid progress in digital innovation.

Semiconductors have evolved considerably in recent years. Some examples of the main uses of semiconductors and their advances are:

Transistors

Transistors serve as the essential components of contemporary electronics, facilitating the amplification and regulation of electrical signals. Transistors, are semiconductors present in various devices, including televisions, radios, computers, and cell phones (Burkacky et al., 2022). In recent years, there has been a substantial rise in the number of transistors incorporated into these devices, primarily as a result of advancements in circuit complexity, miniaturisation and high demanding computation requirements. Integrated circuits are the products that use the largest number of transistors, the most popular of which are the following:

- **Central Processing Units (CPUs):** Within the domain of Central Processing Units, the shift towards diminutive and more proficient transistors has substantially enhanced processing capability (Lotfi-Kamran & Sarbazi-Azad, 2018). Modern CPUs, including Intel's and AMD's processors, are produced utilising state-of-the-art techniques that involve transistors as tiny as 5 nanometres (Munger et al., 2023). The decrease in size enables greater transistor density on a single chip, resulting in improved performance and less power usage (Lotfi-Kamran & Sarbazi-Azad, 2018).
- **Graphics Processing Units (GPUs):** Are designed for parallel processing in graphics rendering and sophisticated computations, have made significant progress due to its complex architecture (Cheng & Gen, 2019). Contemporary graphics processing units manufactured by firms such as Nvidia and AMD are currently built with billions of transistors on production nodes as small as 5 nm (Dally et al., 2021). The GPUs, such as Nvidia's RTX 4090, have significant processing capacity with Ada microarchitecture (Fumero et al., 2024). They also support advanced features like real-time ray tracing and AI-powered apps

(Schillaci, 2024). The reduction in size of transistors and the augmentation of processing cores have facilitated GPUs in efficiently rendering high-resolution graphics and executing intricate computations (Cheng & Gen, 2019).

- **Random Access Memory (RAM):** RAM is essential for temporarily storing data that is accessible by the CPU, has undergone major developments as a result of progress in semiconductor technology (Nair, 2015). Modern RAM modules, such DDR5, use thinner and more densely arranged transistors and capacitors, enabling faster speeds and larger storage capacity (Lehmann & Gerfers, 2017). These improvements are crucial for managing the demanding requirements of modern computer systems.
- **Solid-State Drives (SSDs):** SSDs have significantly gained advantages from advancements in semiconductor technology, particularly by utilising NAND flash memory (Mielke et al., 2017). SSDs employ transistors in their memory cells to deliver rapid and dependable storage (Iaculo et al., 2010). The implementation of 3D NAND technology, which vertically arranges memory cells, has greatly enhanced storage density and capacity in smaller dimensions (C. Liu et al., 2021).

Diodes

Diodes, which are essential elements in semiconductor technology, have made notable progress, especially in the fields of light-emitting diodes (LEDs) and high-efficiency power diodes (Q. Wu et al., 2021; Yam & Hassan, 2005). LED technology has made significant progress in terms of efficiency, resulting in the development of brighter light while simultaneously reducing both thermal output and energy consumption (Kusuma et al., 2020). The advancement in technology has made it easier to use various applications, such as general illumination, digital screens, and vehicle lighting systems (Zissis et al., 2021). Moreover, the advancements achieved in silicon carbide (SiC) diodes signify a significant achievement in the field of power electronics (Xu et al., 2021). Silicon carbide (SiC) diodes have the capacity to function effectively at elevated voltages and temperatures, rendering them highly suitable for challenging applications like electric vehicles and power management in renewable energy systems (Xu et al., 2021).

Sensors

Sensors are employed to detect and measure physical quantities or changes in the environment (D'Amico & Di Natale, 2001).

The advancements in semiconductor technology have greatly enhanced sensor technology, resulting in the creation of more accurate, smaller, and energy-efficient sensors. MEMS sensors have revolutionised various industries by facilitating the use of extremely sensitive and small devices in consumer electronics, automotive systems, and industrial automation (Liao, 2021). For example, modern motion sensors utilised in smartphones possess the capability to accurately detect minuscule movements and changes in direction (Xing et al., 2022). The increasing number of intelligent devices and the Internet of Things (IoT) are continuously pushing forward the progress and integration of sensors with improved functionalities (Krishnamurthi et al., 2020).

Display panels

The field of display technology has experienced rapid and substantial expansion, mostly because to breakthroughs in semiconductor materials and fabrication methods. Significant advancements in display technology have been made with the development and implementation of organic light-emitting diodes (OLEDs) and micro-LEDs (Miao et al., 2023). These developments provide enhanced colour accuracy, brightness, and energy efficiency in comparison to conventional liquid crystal displays (LCDs) (Chansin, 2021). The small and flexible nature of OLED technology has resulted in its widespread adoption in high-end smartphones, televisions, and wearable gadgets. Micro-LEDs, a nascent technology, have the capability to offer enhanced performance characterised by increased luminosity and extended durability (Miao et al., 2023). In addition, the ongoing advancements in semiconductor technologies are enabling the development of higher display resolutions, such as 8K, and enhancements in refresh rates (Shin et al., 2021).

Solar Photovoltaic panels

Traditionally, silicon photovoltaic cells have been the predominant choice in the solar panel industry (Bosio et al., 2020). According to Bosio et al. (2020), renowned for their robustness and efficacy, these cells frequently attain efficiencies close to 22% and have been utilised as the foundation for solar arrays in residential, commercial, and utility-scale settings. Silicon has been the primary material for solar energy development for many years because of its dependable performance and cost efficiency (Dallaev et al., 2023).

Perovskite materials, a recently discovered and proved types of semiconductors, have recently emerged as a groundbreaking advancement in solar energy (Olaleru et al., 2020). Perovskite solar cells, as Olaleru et al. (2020) exhibit, have quickly received acclaim for their capacity to attain efficiencies over 24% in controlled laboratory settings, surpassing conventional silicon cells. Also, they describe how this new technology also can be produced at a much lower cost.

According to Statista (2023) he solar industry has experienced substantial growth, with the total global capacity of solar installations surpassing 1,000 gigawatts (GW). The growth of the solar energy sector is additionally propelled by emerging technologies like bifacial panels, capable of harnessing sunlight from both sides, and tandem cells, which employ stacked layers to absorb a broader range of light wavelengths (Lehr et al., 2020) or other complementary technologies as solar trackers (Hammoumi et al., 2022). These developments are vital for bolstering the importance of solar energy in the transition towards sustainable energy sources, thus leading to an upsurge in the utilisation of semiconductors.

2.3. Key industry players and market outlook

The semiconductor industry is meticulously structured into several sectors based on the many stages of its supply chain (Khan et al., 2021). The supply chain of the semiconductor industry is divided into several distinct stages. The process commences with the design phase, wherein sophisticated tools are employed to create intricate designs and functional specifications for semiconductor devices (White et al., 1997). Following that, the production process begins, utilising sophisticated techniques such as photolithography and etching to produce high-quality semiconductor wafers of extraordinary calibre (Akcalt et al., 2001). Subsequently, these wafers go through assembly, packaging, and comprehensive testing, leading to their conversion into fully functional semiconductor products (Tummala et al., 1997). The distribution stage oversees the global logistics and delivery of these commodities to various markets, showcasing the complex and comprehensive structure of the industry's supply chain.

According to Quart (Karlsson, n.d.), the semiconductor industry is organised into different segments throughout the value chain, which include:

- **Integrated Device Manufacturers (IDMs)** are companies that manage the entire semiconductor device manufacturing process, including design, production, and testing. The main participants consist of Intel Corporation, Texas Instruments Incorporated, Samsung Electronics Co., STMicroelectronics N.V., and Infineon Technologies AG.

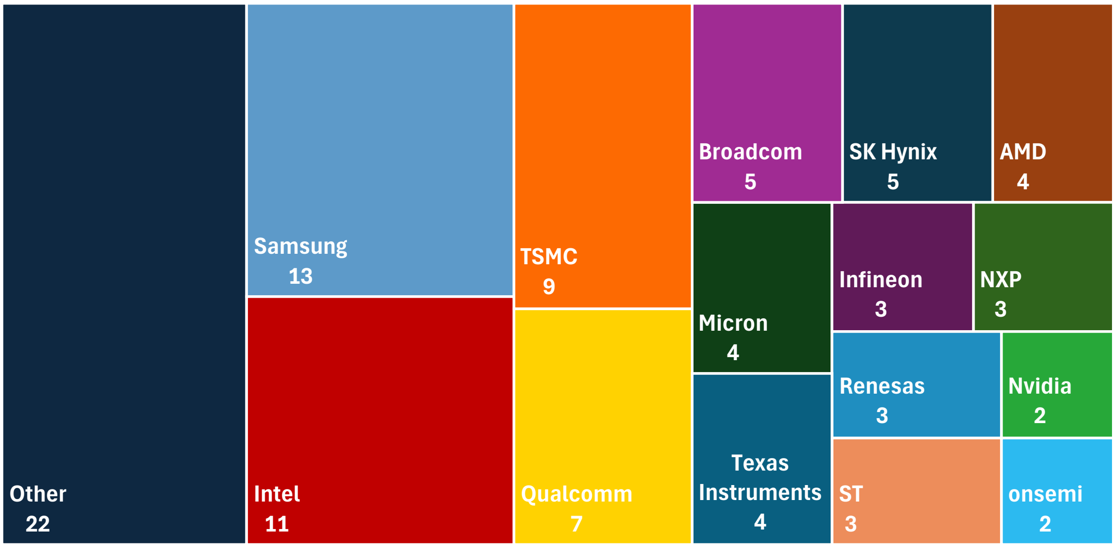
- **Fabless semiconductor companies** are enterprises that focus solely on the design and progress of semiconductor chips, while delegating the manufacturing process to external foundry partners. The indicated companies include NVIDIA Corporation, Qualcomm Incorporated, Broadcom Inc., Advanced Micro Devices, Inc. (AMD), and MediaTek Inc.
- **Foundries** are dedicated facilities that manufacture semiconductor devices based on designs provided by customer companies. The highlighted businesses include Taiwan Semiconductor Manufacturing Company (TSMC), Samsung Electronics Co., GlobalFoundries Inc., United Microelectronics Corporation (UMC), and Semiconductor Manufacturing International Corporation (SMIC).
- **Semiconductor equipment manufacturers** are companies that fabricate the complex apparatus and tools required for the production of semiconductors. The highlighted businesses include Applied Materials, Inc., ASML Holding N.V., Lam Research Corporation, Tokyo Electron Limited, and KLA Corporation.
- **Outsourced Semiconductor Assembly and Test (OSAT) companies** are businesses that provide semiconductor assembly and test services to external entities. The mentioned firms include ASE Technology Holding Co., Amkor Technology, Inc., JCET Group Co., Ltd., Siliconware Precision Industries Co. (SPIL), and Tianshui Huatian Technology Co., Ltd.
- **EDA** firms are organisations that provide specialised software tools and services for the construction and development of electronic systems and circuits. The cited businesses include Cadence Design Systems, Inc., Synopsys, Inc., Siemens (Mentor Graphics), ANSYS, Inc., and Keysight Technologies, Inc.

According to Statista (2023), the semiconductor sector is expected to have a substantial growth in sales of more than 30% by 2027, and the primary factor driving this rise is the expansion of the integrated circuits segment. The integrated circuit industry holds significant significance, as these devices serve as the fundamental building blocks in various advanced technological applications, such as computers, cellphones, and servers as a result of their exceptional functionality and ability to integrate (Burkacky et al., 2022).

The figure 1, depicts the allocation of market share among prominent semiconductor manufacturer companies, thereby showcasing the supremacy of key participants and the competitive environment within the industry. Notably, Samsung, Intel, TSMC, and

Qualcomm are the key participants in the business, collectively holding a 40% market share.

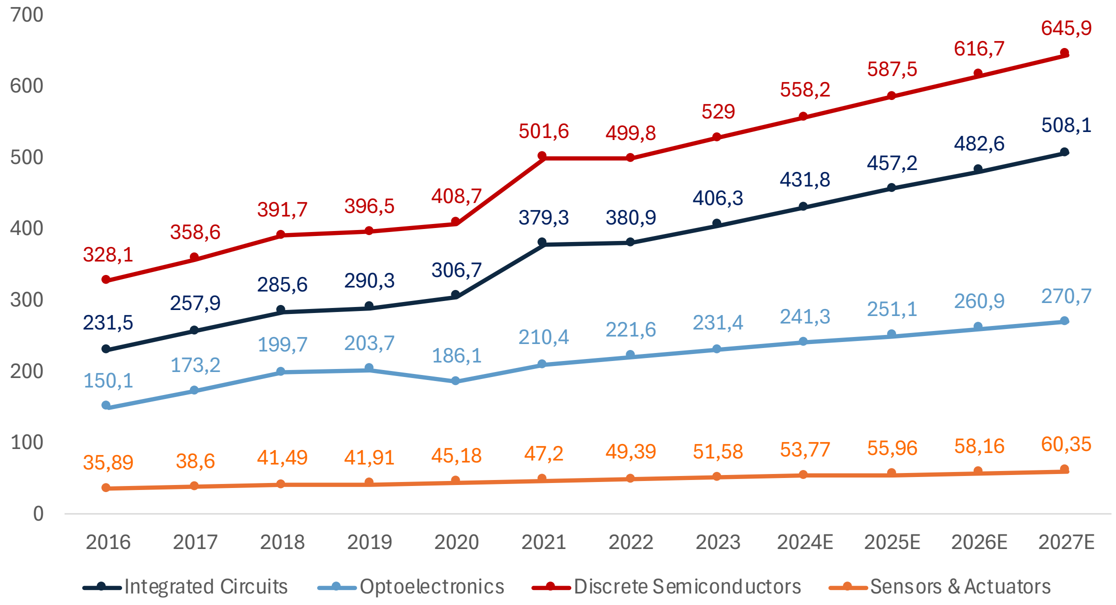
Figure 1. Semiconductors Manufacturers Market Share



Source: Own elaboration based on Statista (2023)

The figure 2 illustrates the past and predicted worldwide sales of semiconductors, with integrated circuits anticipated to reach a staggering 645.9 billion units by the year 2027E. This increase demonstrates the fundamental importance of these elements in intricate electrical systems. Moreover, the data clearly shows a substantial rise in the manufacturing of optoelectronics as new technologies are being developed (Dong et al., 2023), with a predicted quantity of 270.7 billion units. This technology is utilised in LED lighting (Pandey & Mi, 2022) and fiber-optic systems (Chen et al., 2021), as well as in discrete semiconductors, which are projected to increase to 508.1 billion units. The anticipated output of 60.35 billion units of sensors and actuators holds significant significance within the realm of the Internet of Things (IoT) (Krishnamurthi et al., 2020) and industrial automation.

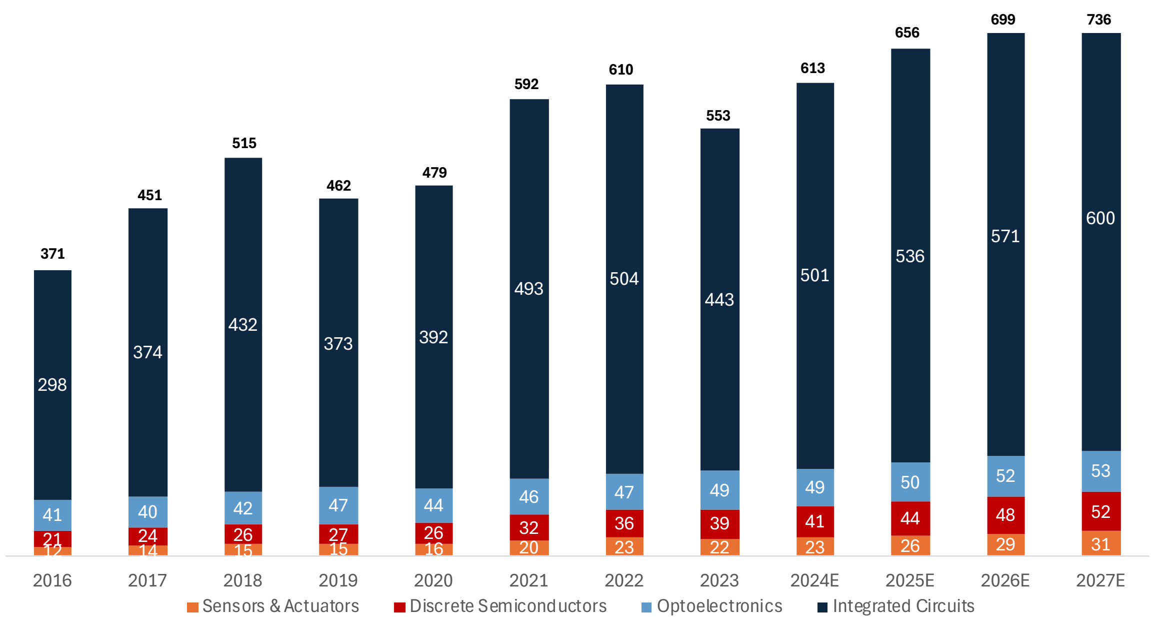
Figure 2. Semiconductors billion units by type



Source: Own elaboration based on Statista (2023)

The figure 3 depicts the increase in revenues of several types of semiconductors, highlighting the rising demand for integrated circuits, optoelectronics, discrete semiconductors, and sensors and actuators (Statista, 2023).

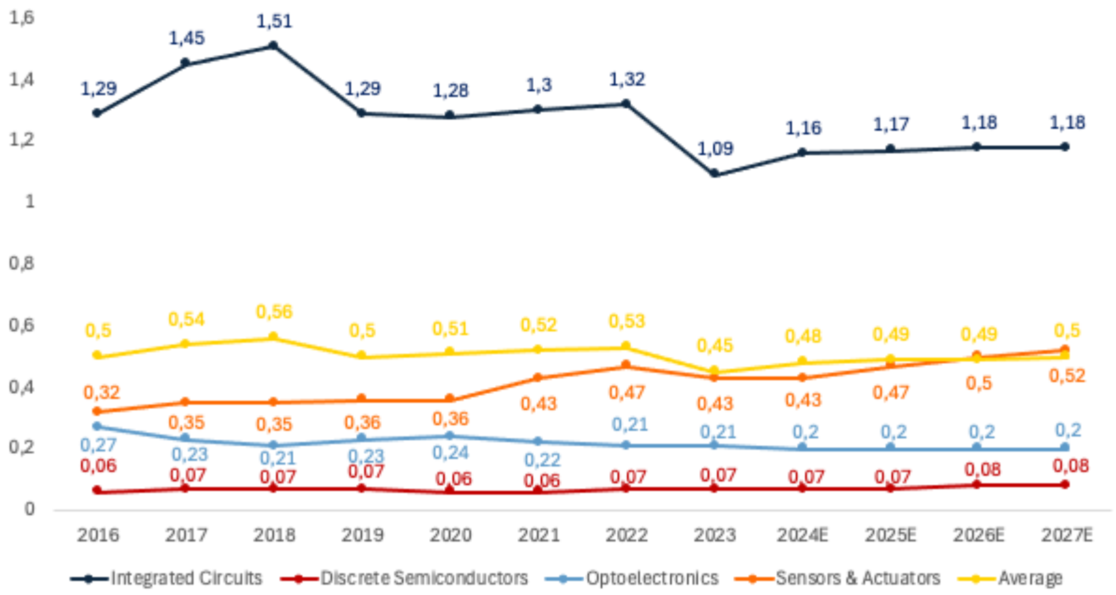
Figure 3. Semiconductors revenue by type



Source: Own elaboration based on Statista (2023)

The figure 4 illustrates the price per unit (in $) for different semiconductor categories spanning from 2016 to 2027E, suggesting a projected stabilization in pricing. This trend signifies enhanced production efficiencies and the expanding acceptance of semiconductor technologies (Varas et al., 2021), which have substantial ramifications for worldwide technology costs and market accessibility.

Figure 4. Semiconductors price per unit by type



Source: Own elaboration based on Statista (2023)

The 2024 Global Semiconductor Business Outlook report by KPMG predicts substantial expansion in the semiconductor sector. Based on a study of 172 high-ranking executives, 83% of them expect a rise in revenue for their companies, indicating a strong and positive financial forecast. The cause of this positive outlook can be linked to several main factors: the incorporation of generative artificial intelligence (Gen AI), the increasing need for semiconductors in the automotive industry, and significant investments in both cloud computing and aerospace sectors (KPMG, 2024).

Notwithstanding these favourable growth prospects, the research emphasises an ongoing and substantial obstacle: the challenge of attracting and maintaining talented personnel. For three consecutive years, this problem has been the main concern of the sector, highlighting the crucial importance of strategic talent management. Therefore, the industry's progress and innovation are dependent on the crucial aspect of being able to attract and cultivate a highly proficient workforce (KPMG, 2024).

Hence, the sustained prosperity of the semiconductor industry in 2024 would depend not only on technological progress and market growth, but also on efficiently resolving the scarcity of skilled workforce. Effectively addressing personnel difficulties is essential for maintaining consistent growth and promoting future innovations (KPMG, 2024).

The "2024 Global Semiconductor Industry Outlook" by Deloitte forecasts a 13% increase in worldwide semiconductor sales, with a potential value of $588 billion. The expansion is fueled by a surge in demand for personal computers, smartphones, and the use of generative AI in diverse areas, such as automotive and industrial applications. The semiconductor industry's crucial position in the global economy is emphasised by these improvements (Deloitte, 2024).

Nevertheless, the research cautions of substantial obstacles that could impede advancement. Geopolitical tensions and vulnerabilities in the supply chain are significant concerns, as they have the potential to disrupt commerce and operations. Deloitte highlights the significance of implementing adaptable solutions to respond to market fluctuations and suggests enhancing the robustness of supply chains by diversifying geographically and boosting domestic production capabilities. It is essential to tackle these problems in order to sustain growth and remain competitive in a continuously changing technology environment (Deloitte, 2024).

3. Fractal Methodology in the EMH

3.1. Fractal Methodology, main uses and relation with EMH

The Efficient Market Hypothesis states that in its weak form, markets are efficient when prices fully reflect all previous trading information, making it challenging to anticipate future price changes merely based on historical data (Fama, 1970; 1991). As to the Efficient Market Hypothesis , the unpredictable nature of asset prices is a result of their random walk behaviour, where each price movement is independent to previous onesa and, therefore, it can be inferred that investors are unable to continuously attain returns that are higher than the average by analysing past prices (Malkiel, 1973, 1989; Jensen, 1978).

Fractal analysis presents a strong opposing viewpoint to this notion by emphasising the existence of long-term interconnections in financial time series (Hurst, 1951). Fractal analysis, first introduced by Hurst (1951) in his research of Nile River water levels, is a method used to identify self-similar patterns in time series data. This analysis reveals that short-term and long-term behaviours exhibit comparable characteristics. In 2005, Mandelbrot expanded upon these ideas in the field of finance, showing that asset values frequently have fractal characteristics. These characteristics can manifest as either persistent, long-term trends or anti-persistent, mean-reverting behaviours, which are not explained by classical theories (Mandelbrot, 2005).

In order to measure these fractal characteristics, we employ the Hurst exponent (H). The Hurst exponent is a crucial metric used in fractal analysis to quantify the extent of long-term memory or reliance in a time series (Graves et al., 2017). Its definition by Hurst (1951) falls between 0 and 1:

- A value of H=0.5 signifies a random walk, which aligns with the Efficient Market Hypothesis and implies the absence of long-term correlation.
- A value of H<0.5 indicates anti-persistence, meaning that the series has a tendency to return to its average, suggesting a greater probability of price reversals.
- A value of H>0.5 indicates persistence, which implies that past trends are expected to remain. This contradicts the Efficient Market Hypothesis by claiming that prior data can be utilised to forecast future movements.

The Rescaled Range (R/S) analysis is the traditional approach for computing the Hurst exponent. This methodology has been extensively utilised to evaluate the effectiveness of the market in many types of assets, such as commodities, energy markets, and cryptocurrencies (Kristoufek & Vosvrda, 2014; Sensoy & Hacihasanoglu, 2014; Jiang et al., 2018). These studies frequently identify deviations from the Efficient Market Hypothesis , indicating that markets display intricate, self-similar patterns throughout time.

It is essential to comprehend these fractal aspects within the semiconductor industry. The semiconductor industry is distinguished by swift technical progress, cyclic demand patterns, and notable interruptions in the supply chain as described by KPMG (2024) and Deloitte. (2024). These characteristics may lead to times of inefficiency during which historical price information could be utilised to predict future patterns (Voas et al., 2021; Burkacky et al., 2022). Our objective is to use fractal analysis on the VanEck Semiconductor UCITS ETF and its components to see if the market demonstrates persistent or mean-reverting behaviours. This will help us evaluate its alignment with the Efficient Market Hypothesis.

4.2. Previous research

Fractal analysis has a long and significant history in financial markets, dating back to Hurst's pioneering research in 1951 on the storage capacity of long-term data. Mandelbrot (2005) applied fractal theory to finance, which enhanced our comprehension of market behaviours that depart from the Gaussian assumptions that underlie the Efficient Market Hypothesis . These fundamental works have sparked countless investigations into the existence of fractal patterns and long-term interdependencies in different markets.

Di Matteo et al. (2003, 2005) showed that financial markets frequently display multifractal behaviour, characterised by distinct scaling rules that apply to various parts of the data. Kristoufek (2010) conducted a more in-depth analysis of the fractal patterns in financial time series, with a particular focus on the influence of long-term memory on asset returns. These works highlight the significance of fractal analysis in questioning the Efficient Market Hypothesis by presenting evidence of enduring and opposing patterns in markets.

In recent times, there has been a shift in research towards examining particular sectors and asset classes. New methodologies have also been introduced, such as DFA (Grivel et al., 2021) or GHE, which incorporate new factors in the assessment of market efficiency.

For example, in the fuel and energy industry, David et al. (2020), Tiwari et al. (2021), Ftiti et al. (2020) and Ali et al. (2021) have carefully analysed efficiency using different types of fractal methods such as DFA.

Takaishi and Adachi (2019), López-Martín et al. (2021), and Mikhaylov et al. (2021) have used the Fractal methodology to asses if the Cryptocurrencies market is efficient or not.

On the other hand, other studies have been carried out to try to assess whether some indices are efficient, e.g. Bui and Ślepaczuk (2022) try to identify mean-reverting patterns in the Nasdaq100, while Vogl (2023) tries to assess the efficiency of the S&P500 using fractal methods such as MFDFA combined with a rolling window.

Finally, some studies have been carried out on industries that can also be classified at a high level as technological companies. For example, Mulligan (2004) applies the fractal methodology to technology companies, some of which are included in our analysis, such as Texas Instruments.

Our study utilises these insights in the context of the semiconductor sector. Through an examination of the VanEck Semiconductor UCITS ETF and its component companies, our objective is to ascertain if this sector conforms to or diverges from the concepts of the Efficient Market Hypothesis .

4.3. Data collection and preparation

We focused our analysis on the VanEck Semiconductor UCITS ETF (SMGB.L) and its 25 constituent stocks. The dataset contains daily adjusted closing prices spanning from December 11, 2020, to June 11, 2024. This time frame spans 898 trade days, which offers a substantial and reliable dataset for doing fractal analysis. The adjusted closing prices are utilised to incorporate any corporate actions, such as dividends and stock splits, in order to ensure that the data accurately represents the actual market worth of the assets.

Data preprocessing refers to the steps taken to clean and transform raw data into a format that is suitable for analysis. In order to guarantee the precision and comprehensiveness of our study, we executed multiple preprocessing procedures:

- Dealing with Missing Data: We employed linear interpolation to replace any absent values in the time series (Kay, 1983). This approach preserves the general pattern and prevents the introduction of substantial biases that could skew the fractal analysis.

- Calculating Logarithmic Returns: The price data was converted into logarithmic returns (r_t), which were calculated using the formula:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

4.4 The Hurst exponent and rescaled range (R/S) analysis.

In our research, we employed a minimum lag (n) of 10 days and a maximum lag equal to half the duration of the data series, which was 449 days. This range encompasses both immediate and prolonged interconnections while accommodating the limitations of the sample size.

To investigate the long-term dependencies in the semiconductor market, we employed the Rescaled Range (R/S) analysis to calculate the Hurst exponent. This method involves several steps as Weron (2002) and Corzo Santamaría et al. (2022) exhibit:

- Dividing the Time Series: The time series is divided into d subseries of length nn. For each subseries $Z_{i,m}$ (where i=1,...,n and m=1,...,d) the sample mean (E_m) and standard deviation (S_m) are computed.
- Normalization: The data points are normalized by subtracting the sample mean, yielding $X_{i,m} = Z_{i,m} - E_m$.
- Constructing the Cumulative Time Series: The cumulative time series is then constructed as $Y_{i,m} = \sum_{j=m}^{i} X_{j,m}$ Yi,m=$\sum j$=$1iXj,m$.

The Rescaled Range (R/S) statistic is defined by the formula:

$$\frac{R}{S} = \frac{\max(Z_{1,m}, \ldots, Z_{n,m)} - \min(Y_{1,m}, \ldots, Y_{n,m})}{S(n)}$$

- Averaging the Rescaled Range: The mean rescaled range for all subseries of length nn is computed, yielding the $R/S(n)$ statistic.
- Log-Log Plotting: Finally, we plot log($R/S(n)$) against log(n). The slope of the linear fit to this log-log plot provides the Hurst exponent H:

$$R/S(n) = C * n^H$$

Where C is a constant.

For our analysis, we selected a minimum lag (n) of 10 days and a maximum lag of half the duration of the data series to be able to capture short term trends (449 days). This range incorporates both short-term and long-term dependence while accommodating the sample size limits.

In order to verify the accuracy of our findings, we created 10,000 artificial Gaussian white noise series that were of same length to the financial data as used by Corzo Santamaría et al. (2022). We computed the Hurst exponent for each synthetic series and determined the values corresponding to the 5th and 95th percentiles in order to establish confidence intervals. This comparison enables us to evaluate if the observed Hurst exponents depart significantly from those anticipated under the random walk hypothesis.

The Hurst exponent's value ranges from 0 to 1, where H>0.5 indicates persistent behavior (trending), H=0.5 suggests a random walk, and H<0.5 denotes anti-persistence or mean-reverting (Corzo Santamaría et al., 2022).

4.5. Rolling window analysis

In order to examine the changes in market efficiency over time, we conducted a rolling window analysis as used in several studies like Vogl (2023). This approach entails the computation of the Hurst exponent using a moving window of a predetermined size. In our analysis, we selected a window size of 252 trading days, which is roughly equivalent to one year. We then moved the window forward by one day at a time to provide daily data, ensuring a higher level of accuracy in capturing trends.

The Hurst exponent was calculated for each window using the R/S analysis. This methodology offers a dynamic viewpoint on market efficiency, enabling us to see the evolution of persistence or mean-reversion behaviours in response to fluctuations in market conditions and external events.

4.6. Statistical significance and confidence intervals; Gaussian white noise

In order to determine the statistical significance of our results, we created 10,000 synthetic Gaussian white noise series as used by Corzo Santamaría et al. (2022). Each series had a length of 898 observations, which matched our dataset, allowing for a fair comparison. We computed the Hurst exponent for each artificial series using the identical R/S analysis approach.

The synthetic Hurst exponents were utilised to determine the lower and upper bounds of the 5th and 95th percentiles, thereby creating a 90% confidence interval for the Hurst exponent. This was done on the assumption of a random walk (H = 0.5) for our particular situation. The empirical Hurst exponents of the ETF and its components were subsequently compared to these boundaries to ascertain whether they had notable departures that suggest either persistent or mean-reverting behaviour.

4. Sample Description

4.1. Definition and main characteristics

While the materials that make up semiconductors can be traded as commodities, such as silicon and gallium, semiconductors themselves cannot be traded. In this sense, semiconductors can be traded through various financial instruments. The two main ways to invest are through the companies that produce semiconductors, companies that use them in their products, or through an Exchange-Traded Fund (ETF), mutual fund or index that includes some of the companies involved in the industry.

At present, there are numerous indexes and mutual funds that incorporate semiconductor businesses in its components, such as the SP500 or Nasdaq. However, to focus just on analysing the semiconductor industry, the chosen index is the VanEck Semiconductor UCITS.

An ETF is a financial instrument that combines multiple stocks, bonds, or commodities into a single entity, traded on stock exchanges and its value corresponds to the net asset value of the underlying assets (Gastineau, 2002). ETFs are characterized for their low costs, inherent diversification, and high liquidity and unlike mutual funds, ETFs trade on stock exchanges like individual stocks, allowing investors to buy and sell shares at market prices through traditional and online brokers (Abner, 2016; Hill et al., 2015).

Based on Ferry´s (2007) study, ETFs are designed to mirror the performance of specific indices, commodities, or asset classes, thus offering intrinsic diversification across a range of assets. However, investors in ETFs must accept all assets within the fund as they are (Ferri, 2007).

According to Brown et al. (2020) ETFs rely on authorized participants (APs) to maintain price alignment with their net asset value (NAV). APs create or redeem ETF shares by trading underlying assets with the ETF issuer based on market demand fluctuations and by process keeps the ETF's market price in line with its NAV (Brown et al., 2020).

Depending on their specific policies, ETFs may distribute dividends or interest from the underlying assets, adding to the overall return along with any capital gains from asset value appreciation (Chen & Kien, 2019; Deville, 2008).

The primary costs for ETF investors include commissions and the expense ratio (Ferri, 2007). Many trading platforms now offer commission-free ETF trading, reducing this cost. The expense ratio, an annual fee based on a percentage of the ETF’s assets, covers management and administration expenses, directly affecting returns and unlike mutual funds, ETFs usually do not charge "load" fees, making them more cost-effective (Angel et al., 2016).

4.2. ETF: VanEck Semiconductor UCITS, specifications and components

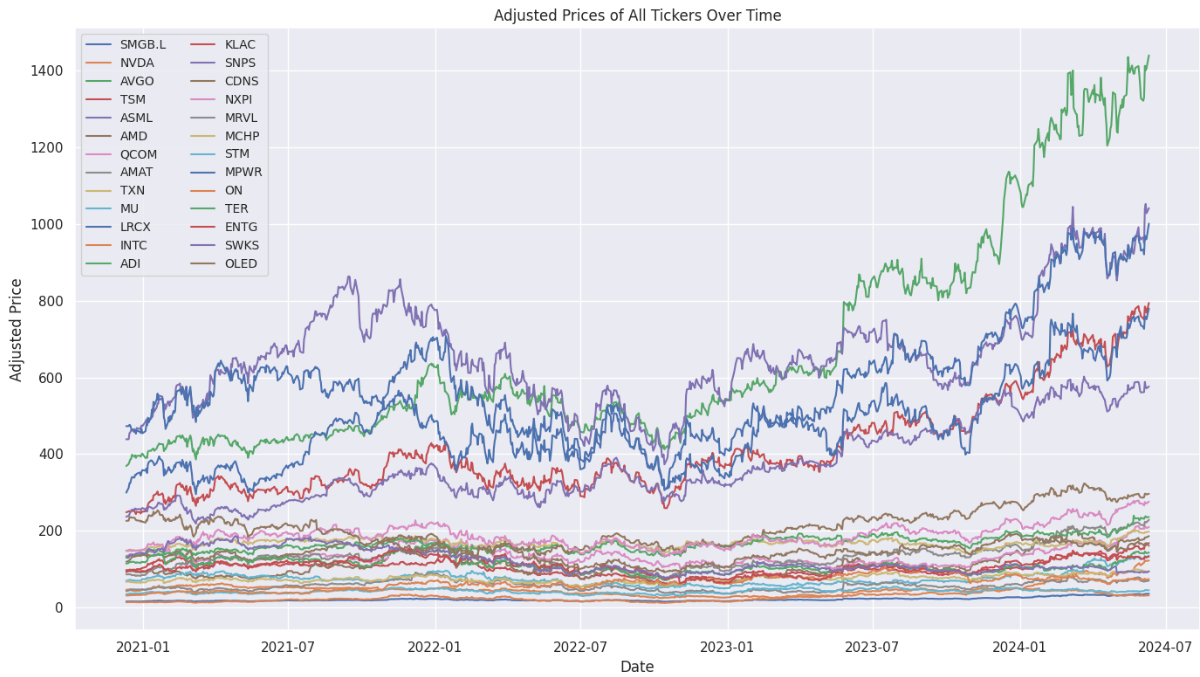
The VanEck Semiconductor ETF UCITS, denominated in USD, and with ISIN number IE00BMC38736, seeks to replicate the performance of an internationally diverse selection of semiconductor manufacturing and equipment businesses by tracking the "MVIS US Listed Semiconductor 10% Capped ESG Index". The ETF allows potential investors to invest in a diversified portfolio of stocks from different companies within the industry, thereby reducing risk (Evans & Archer, 1968).

The ETF was launched on 1 December 2020 and had a NAV of $2.4 billion with 50.4 million outstanding shares as of 16th June 2024 (Semiconductor ETF | SMH | VanEck, 2024). As of June 2024, the ETF is registered in 16 countries and has a total of 25 holdings. According to the prospectus and Fact Sheet, it has a total expense ratio of 0.35% and is rebalanced twice a year with monthly adjustments, on selection days, each index component is equally weighted within specific constraints. The ETF's performance and that of its constituents have been tracked since its inception, and as of 16th June 2024, has a YTD return of 39,81%.

Companies must fulfil strict criteria, as outlined in the ETF's prospectus and Fact Sheet, in order to be included in this ETF. These criteria encompass two conditions: generating a minimum of 50% of their income from semiconductor-related operations and being integrated into the semiconductor supply chain. If a company's semiconductor revenue falls below 25%, it may be eligible for elimination.

In addition, companies are required to maintain a minimum market capitalization and trading volume in order to guarantee the liquidity of the ETF. The ETF additionally screens out firms that contravene UN Global Compact Principles or get substantial revenue from contentious industries such as thermal coal, fossil fuels, and tobacco, thereby guaranteeing adherence to socially responsible investment principles. These conditions guarantee that the ETF precisely mirrors the semiconductor industry and strictly follows rigorous ethical guidelines (Semiconductor ETF | SMH | VanEck, 2024)..

Figure 5. Performance of the ETF and its components since ETF inception to 11-06-2024



Source: Own elaboration based on historical data (11-12-2019 to 11-06-2024)

The graph shown in Figure 5 illustrates the modified price paths of the VanEck Semiconductor UCITS ETF (SMGB.L) and its constituent parts from December 2020 to June 2024. NVIDIA (NVDA) and ASML (ASML) demonstrate significant increase, reflecting high investor interest and strong performance during the period. In contrast, stocks such as Intel (INTC) and Texas Instruments (TXN) exhibit relatively modest price gains. AMD and Micron (MU) exhibit more price volatility, which is indicative of the dynamic market conditions in their respective areas. The price fluctuations in the semiconductor industry's many segments, as outlined in Table 1, demonstrate the diverse performance and market responses within the industry.

Table 1. VanEck Semiconductor UCITS ETF and components; Data and descriptives

Ticker	Name	Sector - Industry Segment	Nº Observations	Nº Shares	Market Value	Weight (%)	Mean (%)	Std (%)	Max (%)	Min (%)	Skew	Kurtosis	Jarque-Bera test
SMGB.L	VanEck Semiconductor UCITS ETF	ETF	898				0,09	1,75	7,47	-6,34	-0,03	0,95	33,74 (***)
ADI	Analog Devices Inc	Integrated Device Manufacturers (IDMs)	898	811897	85765947.21	3,65	0,06	1,87	10,31	-8,16	0,08	2,00	150,34 (***)
AMAT	Applied Materials Inc	Semiconductor Equipment Manufacturers	898	1477113	209553913.01	8,92	0,11	2,60	10,46	-8,38	0,00	0,56	11,91 (***)
AMD	Advanced Micro Devices Inc	Fabless Semiconductor Companies	898	908589	105791860.49	4,5	0,06	3,13	13,34	-14,93	0,00	1,63	99,93 (***)
ASML	ASML Holding NV	Semiconductor Equipment Manufacturers	898	344989	299423565.06	12,75	0,10	2,51	13,60	-7,64	0,13	1,44	79,91 (***)
AVGO	Broadcom Inc	Fabless Semiconductor Companies	898	1155912	319128526.48	13,31	0,15	2,06	10,90	-7,24	0,36	1,89	152,29 (***)
CDNS	Cadence Design Systems Inc	EDA Firms	898	102899	20714729.79	0,88	0,10	2,06	9,73	-8,29	0,07	1,57	93,37 (***)
ENTG	Entegris Inc	Semiconductor Equipment Manufacturers	898	80818	8131894.20	0,35	0,04	2,93	17,91	-23,53	-0,32	6,63	1657,94 (***)
INTC	Intel Corporation	Integrated Device Manufacturers (IDMs)	898	2818051	85095357.54	3,62	-0,04	2,29	10,13	-12,68	-0,45	3,63	524,55 (***)
KLAC	KLA Corporation	Semiconductor Equipment Manufacturers	898	180203	90097509.38	3,83	0,13	2,51	8,71	-7,88	0,02	0,62	14,36 (***)
LRCX	Lam Research Corporation	Semiconductor Equipment Manufacturers	898	137887	73081720.73	3,11	0,08	2,67	11,49	-9,05	-0,01	1,07	42,80 (***)
MCHP	Microchip Technology Inc	Integrated Device Manufacturers (IDMs)	898	31682	25409462.40	1,08	0,04	2,36	10,58	-8,59	0,00	0,70	18,27 (***)
MPWR	Monolithic Power Systems Inc	Fabless Semiconductor Companies	898	273544	135332871.92	5,76	0,11	3,07	16,09	-10,96	0,20	1,90	141,39 (***)
MRVL	Marvell Technology Inc	Fabless Semiconductor Companies	898	445127	33160467.49	1,41	0,06	3,28	28,08	-12,77	0,71	7,15	1986,35 (***)
MU	Micron Technology Inc	Integrated Device Manufacturers (IDMs)	898	533552	34869857.28	1,48	0,07	2,56	13,22	-8,50	0,20	1,38	77,46 (***)
NVDA	NVIDIA Corporation	Fabless Semiconductor Companies	898	2372962	312149526.48	13,31	0,25	3,22	21,81	-10,54	0,48	3,33	449,83 (***)
NXPI	NXP Semiconductors NV	Integrated Device Manufacturers (IDMs)	898	148541	30732789.75	1,31	0,07	2,35	8,58	-8,39	-0,01	0,43	6,87 (**)
OLED	Universal Display Corporation	Semiconductor Equipment Manufacturers	898	31194	6261266.00	0,27	-0,02	2,61	20,47	-11,12	0,49	5,84	1312,90 (***)
ON	ON Semiconductor Corporation	Integrated Device Manufacturers (IDMs)	898	322326	32058279.96	1,36	0,10	3,12	13,45	-24,55	-0,37	4,80	882,07 (***)
QCOM	Qualcomm Inc	Fabless Semiconductor Companies	898	794375	113380383.75	4,82	0,05	2,30	11,98	-9,24	0,01	2,41	216,81 (***)
SNPS	Synopsys Inc	EDA Firms	898	102899	20714729.79	0,88	0,10	2,08	9,76	-6,58	0,28	2,00	162,04 (***)
STM	STMicroelectronics NV	Integrated Device Manufacturers (IDMs)	898	526274	23946063.82	1,02	0,03	2,37	11,65	-8,70	0,05	1,23	56,53 (***)
SWKS	Skyworks Solutions Inc	Fabless Semiconductor Companies	898	102194	11106379.68	0,47	-0,04	2,29	11,80	-16,59	-0,39	4,60	814,63 (***)
TER	Teradyne Inc	Semiconductor Equipment Manufacturers	898	87781	10834820.20	0,46	0,03	2,66	10,73	-25,37	-0,89	9,54	3523,35 (***)
TSM	Taiwan Semiconductor Manufacturing Co	Foundries	898	1466768	256402458.00	10,91	0,06	2,16	11,34	-6,39	0,47	2,06	192,40 (***)
TXN	Texas Instruments Incorporated	Integrated Device Manufacturers (IDMs)	898	591455	91863600.85	3,91	0,03	1,68	6,44	-6,74	-0,06	0,93	32,90 (***)

Source: Own elaboration based on the ETF Website (Semiconductor ETF | SMH | VanEck, 2024). Data updated as of 16 June 2024.

Table 1 provides an extensive examination of semiconductor equities that are part of the VanEck Semiconductor UCITS ETF. The investigation spans from December 11, 2020, to June 11, 2024. The stocks are categorised into different segments based on their responsibilities in the semiconductor value chain. These segments include Integrated Device Manufacturers (IDMs), Fabless Semiconductor Companies, Semiconductor Equipment Manufacturers, EDA Firms, and Foundries (Table 1).

In the ticker column, each stock is denoted by its distinct symbol. For instance, NVDA represents NVIDIA Corporation, a prominent player in the Fabless Semiconductor Companies sector. NVIDIA is renowned for its groundbreaking innovations in graphics processing and artificial intelligence (Table 1). Similarly, the name column presents the full names of these entities, guaranteeing clarity in their identification (Table 1).

The sector-industry segment column classifies each company according to its role within the semiconductor ecosystem (Table 1). Intel Corporation (INTC) and Texas Instruments Incorporated (TXN) are categorised as Integrated Device Manufacturers (IDMs), responsible for overseeing the complete semiconductor production process. On the other hand, firms such as NVIDIA Corporation (NVDA) and AMD are categorised as Fabless Semiconductor firms. They primarily concentrate on the design aspect of semiconductor production and delegate the manufacturing process to external foundries like TSMC (Table 1).

The "Nº observations" column represents the total number of daily price observations, which is consistently set at 898 for all stocks (Table 1). This uniformity enables an equitable evaluation. Regarding the number of shares and market value, these indicators provide information on the ETF's holdings in terms of the count of shares and the valuation in the market, respectively (Table 1). NVIDIA Corporation holds the largest position in the ETF, with 2,372,962 shares and a market value of $312,149,526.48. This highlights its substantial impact on the overall performance of the ETF (Table 1).

The weight column represents the percentage that each stock contributes to the overall value of the ETF, as seen in Table 1. NVIDIA, with a significant weight of 13.31%, plays a crucial role in the portfolio. The mean (%) column displays the average daily logarithmic return. NVIDIA stands out with a mean return of 0.2493%, indicating its strong and consistent growth (Table 1). In contrast, equities such as Intel Corporation (INTC) and Universal Display Corporation (OLED) have marginal negative returns, indicating the presence of obstacles specific to their respective sectors (Table 1).

The Std (%) or standard deviation column (Table 1) captures the measure of volatility. The ETF with the ticker symbol SMGB.L has the lowest level of volatility, measured at 1.7546%. This indicates its ability to provide stability in the market, as seen in Table 1. However, businesses like Marvell Technology Inc. (MRVL) and AMD demonstrate greater volatility, which suggests their high-risk, high-reward characteristics in the industry (Table 1).

The Max (%) and Min (%) columns provide information on the highest and lowest daily returns recorded (Table 1). Marvell Technology Inc. (MRVL) achieved the biggest one-day increase of 28.0836%, while AMD suffered a severe one-day decline of -14.9299%, demonstrating the possibility of significant performance variations in this industry (Table 1).

Skewness and kurtosis offer valuable information about the distribution of returns, as seen in Table 1. Skewness is a statistical metric that quantifies the degree of asymmetry in a distribution. In the case of Intel Corporation (INTC) and ON Semiconductor Corporation (ON), they exhibit negative skewness, which suggests a higher frequency of drops in their values. This information is presented in Table 1. On the other hand, NVIDIA Corporation (NVDA) and Marvell Technology Inc. (MRVL) demonstrate positive skewness, indicating infrequent but significant profits (Table 1). Kurtosis is a measure of the extent to which a distribution has tails, with higher values indicating a higher likelihood of extreme returns for firms such as Marvell Technology Inc. (MRVL) and Entegris Inc. (ENTG) (Table 1).

Finally, the Jarque-Bera test evaluates the normality of the return distributions, as shown in Table 1. The test decisively rejects the null hypothesis of normality for all stocks at a 1% significance level, as indicated by the (***) notation, demonstrating substantial deviations characterised by skewness and kurtosis (Table 1).

To summarise, this comprehensive evaluation emphasises the different levels of performance and risk associated with the semiconductor industry (Table 1). Integrated Device Manufacturers (IDMs) like Texas Instruments Incorporated (TXN) and STMicroelectronics N.V. (STM) demonstrate intermediate profitability and stability. On the other hand, Fabless Semiconductor Companies, such as NVIDIA Corporation (NVDA) and AMD, display high profitability but also higher levels of volatility (Table 1). Semiconductor equipment manufacturers, such as Applied Materials Inc. (AMAT), have a stable performance with a modest level of risk (Table 1). EDA firms such as Cadence Design Systems Inc. (CDNS) and Synopsys Inc. (SNPS) offer stable returns with less volatility, highlighting their crucial involvement in electronic design and development (Table 1).

The top 5 holdings of the ETF account for more than half of its net asset value (NAV), as table 2 illustrates. The portfolio consists of diverse investments across different sectors of the industry, including Nvidia, Broadcom, ASML, TSMC, and AMD.

- **Nvidia** is the dominant corporation in the Graphic Processing Unit (GPU) sector of the business with c.80% market share (M. Chen & Leong, 2022) and their products are renowned for their superior performance and remarkable power efficiency (Choquette et al., 2021). They are specifically engineered for graphic processing, with a special emphasis on video games, video processing, and graphic design, among other related tasks. Nvidia's CUDA technology is an essential platform and programming style for parallel computing (Kondratyuk et al., 2021). It offers developers the necessary tools to fully harness the capabilities of GPU-accelerated computing and its GPUs are employed for artificial intelligence (AI) computation (Cass, 2020; Kelkar & Dick, 2021), a factor that has propelled Nvidia to become one of the most valuable businesses in the market, boasting a market capitalization above $2 trillion (NVIDIA Corporation - Financial Info - 2023 Annual Report, 2024). The company's revenues exceeded $260 billion in both 2022 and 2023.
- **Broadcom** is becoming a leading firm in the semiconductor sector, focusing on various technologies such as networking, broadband, storage, and wireless applications (Wang et al., 2017). This guarantees that its services, such as advanced processors for data centres and network infrastructure, maintain a dominant position in the technology industry (Z. Liu et al., 2023). Broadcom's market capitalization exceeded $600 billion as of March 2024, and it generated $35.8 billion in revenues during FY2023.
- **ASML** is a prominent company in the semiconductor manufacturing industry that specialises in producing photolithography equipment (Fang & He, 2022). Fang and He (2022) highlight how this equipment is crucial to produce sophisticated semiconductor devices. The company's monopoly in supplying Extreme Ultraviolet (EUV) lithography systems highlights its crucial role in advancing chip production, namely in terms of miniaturisation and enhanced efficiency (Meiling et al., 2004). ASML's market capitalization exceeded €360 billion as of March 2024, while its revenues for FY2023 amounted to €7.2 billion.

- **Taiwan Semiconductor Manufacturing Company (TSMC)** specialises in the production of high-performance graphics processing units and a diverse array of semiconductor products (Liu et al., 2005). TSMC plays a crucial role in advancing computers, mobile communications, and artificial intelligence processing as a significant manufacturing partner to the world's leading technological businesses (Hao & Bu, 2022). TSMC's market capitalization exceeded $700 billion as of March 2024, while its revenues for the fiscal year 2023 amounted to $70.3 billion.
- **Advanced Micro Devices, Inc. (AMD)** holds a strong position in the computing and graphics industry, especially with the launch of its Radeon series of graphics cards (M. Chen & Leong, 2022). AMD's dedication to leading advancements in the graphics processor unit industry is in line with its prominent position in the technology field, propelling progress in both computing and graphics rendering capabilities (Kondratyuk et al., 2021). As of March 2024, AMD's Market Capitalization exceeds $270 billion, while its revenues in FY2023 amounted to $6.2 billion.

4.3 Data acquisition and preprocessing

The data used for this analysis has been extracted from Yahoo Finance using the `yfinance` library. It includes information from December 11, 2020, to June 11, 2024. The information contains the adjusted daily closing prices for the VanEck Semiconductor UCITS ETF (SMGB.L) and its 25 components and covers a period of 898 trading days. The adjusted closing prices are essential as they accurately represent the actual market value of the assets, taking into account any company activities such as dividends and stock splits.

We utilised linear interpolation to populate any gaps in the data as it maintains the dataset's durability and consistency with the minimum interpolation error (Kay, 1983). This technique eliminates any possible discontinuities caused by holidays or other days when trading is not conducted, guaranteeing a comprehensive and uniform time series for each stock symbol.

5. Analysis and Results

Table 2. Hurst coefficients for the ETF and the components and IC

Ticker	Hurst Exponent	Number of Observations
SMGB.L	0,47988	898
NVDA	0,60001	898
AVGO	0,516834	898
TSM	0,552789	898
ASML	0,576928	898
AMD	0,574836	898
QCOM	0,470181	898
AMAT	0,522662	898
TXN	0,43758	898
MU	0,453567	898
LRCX	0,514751	898
INTC	0,548174	898
ADI	0,433076	898
KLAC	0,449444	898
SNPS	0,469303	898
CDNS	0,463975	898
NXPI	0,420123	898
MRVL	0,494436	898
MCHP	0,398787	898
STM	0,488768	898
MPWR	0,459916	898
ON	0,441726	898
TER	0,487309	898
ENTG	0,477196	898
SWKS	0,527383	898
OLED	0,43578	898
IC 5	0.4510	
IC 95	0.6467	

Source: Own elaboration based on the Results of the Analysis.

5.1 ETF and components Analysis

This investigation seeks to ascertain the extent to which the semiconductor business, as exemplified by the VanEck Semiconductor UCITS ETF (SMGB.L) and its constituent stocks, conforms to the Efficient Market Hypothesis . In order to accomplish this, we examine the Hurst exponents of these assets. The Hurst exponent (H) is essential for evaluating the long-term memory and fractal properties of financial time series, offering insights into whether price fluctuations adhere to the Efficient Market Hypothesis (Eom et al., 2008).

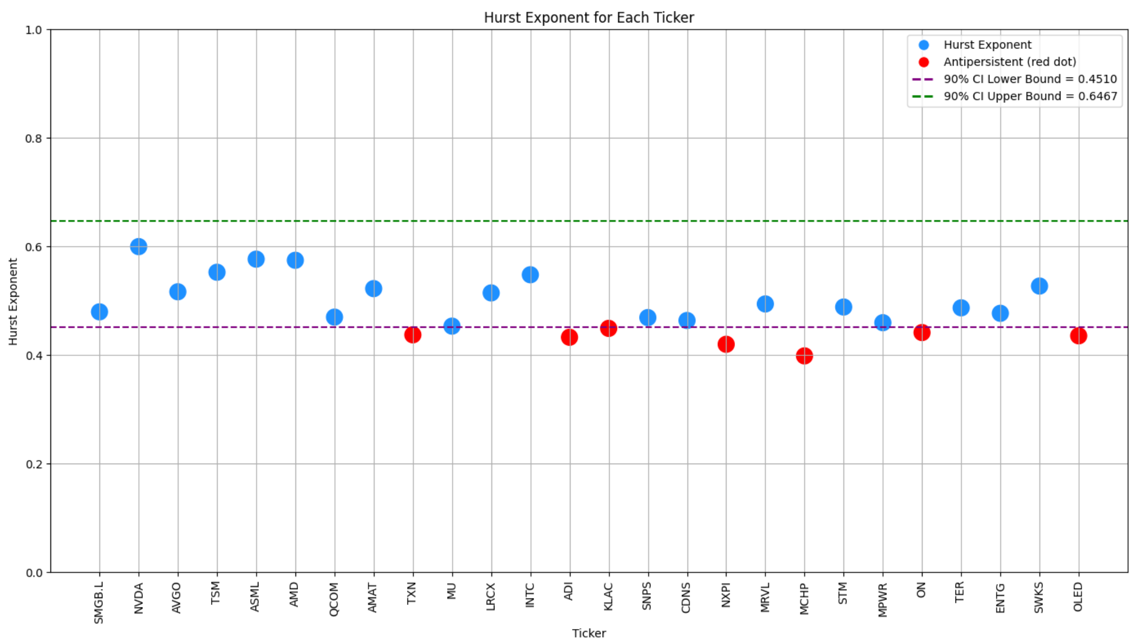
5.1.1. Theoretical Explanation of the Hurst Exponent

The Hurst exponent has a theoretical range of 0 to 1 and its interpretation is as follows according to Hurst (1951) study:

- A value of H = 0.5 indicates a random walk, meaning that the time series does not show any long-term association. This aligns with the idea of market efficiency according to the Efficient Market Hypothesis. In this situation, previous changes in price cannot be used to anticipate future changes, thus preventing the possibility of capitalising on trends for reliable profits.
- If H > 0.5, it indicates persistent behaviour, meaning that trends are more likely to continue. This indicates that the series demonstrates positive autocorrelation, meaning that future price changes are affected by previous moves in the same direction. Consistent behaviour would indicate predictability and, hence, a departure from market efficiency.
- When the value of H is less than 0.5, it suggests the presence of anti-persistent or mean-reverting behaviour, indicating a higher likelihood of trends reversing. This indicates that the series demonstrates negative autocorrelation, meaning that future price movements tend to go against prior moves. The presence of mean-reverting behaviour indicates the potential for predictability and a departure from market efficiency.

5.1.2. Analysis using confidence intervals.

Figure 6. Hurst Coefficient for each Ticker



Source: Own elaboration based on the Results of the Analysis.

In order to evaluate the effectiveness of the semiconductor stocks, we analyse their Hurst exponents in relation to a 95% confidence interval (CI) obtained from their empirical distribution. The confidence interval for these Hurst exponents is [0.4510, 0.6467] as described in table 2. This interval functions as a standard against which other things can be measured:

- Stocks within the confidence interval [0.4510, 0.6467] exhibit random walk behaviour, which is indicative of market efficiency. The fluctuations of these equities are predominantly indeterminate, implying that previous price patterns do not offer dependable insights for predicting future values.
- Stocks with a CI value greater than 0.6467 would demonstrate persistent behaviour. Nevertheless, none of the examined stocks fit into this category, suggesting that they do not possess distinct trend-following attributes that diverge significantly from the random walk model.
- Stocks with a CI value below 0.4510 exhibit anti-persistent or mean-reverting behaviour. These stocks tend to return to their average value after deviating, which contradicts the concept that market movements are random in efficient markets and indicates the possibility of predicting their price changes.

5.1.3. Examination of ETF and its components

The VanEck Semiconductor UCITS ETF (SMGB.L) typically exhibits a rolling Hurst exponent that hovers around 0.5. This indicates that the price changes of the ETF usually conform to random walk behaviour, which is a sign of market efficiency. Periods of deviation, in this context, indicate the combined effects of the underlying components, which display both consistent and fluctuating behaviours at various points in time.

Inside the context of the Confidence Interval, specifically in relation to Random Walk and Efficient Market Behaviour, it is observed both in figure 6 and table 2 that many component stocks are situated inside the 95% confidence interval. This suggests that their behaviour aligns with that of a random walk and so indicates market efficiency. The following companies have been included: - NVIDIA (H = 0.600010) - Taiwan Semiconductor Manufacturing (H = 0.552789) - ASML Holding (H = 0.576928) - Advanced Micro Devices (H = 0.574836) - Intel (H = 0.548174) - Broadcom (H =

0.516834) - Applied Materials (H = 0.522662) - Lam Research (H = 0.514751) - Skyworks Solutions (H = 0.527383) (table 2). The Hurst exponents of these stocks indicate that they adhere to a random walk pattern, rendering their future price movements unpredictable and consistent with the Efficient Market Hypothesis .

Regarding the Confidence Interval (Persistent Behaviour), all equities in this study have Hurst exponents that are below the upper bound of the confidence interval (0.6467). The lack of this presence indicates that none of the stocks have noteworthy trend-following attributes, which would have signalled a departure from the random walk and thus market efficiency.

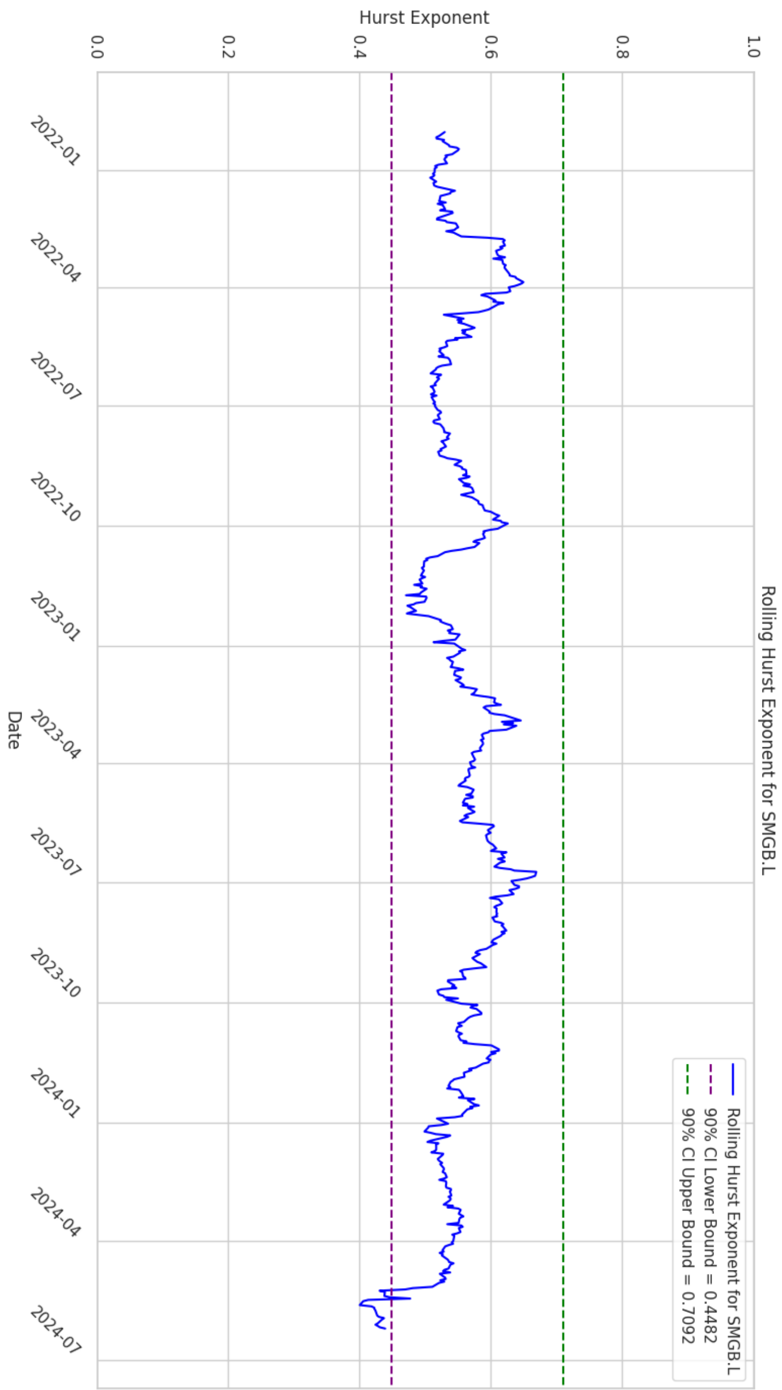
Regarding the Confidence Interval (Anti-persistent, Mean-reverting Behaviour), in table 2 several stocks demonstrate Hurst exponents below the lower bound of the confidence interval, suggesting mean-reverting or anti-persistent behaviour. These stocks include Texas Instruments (H = 0.437580), Analogue Devices (H = 0.433076), KLA Corporation (H = 0.449444), NXP Semiconductors (H = 0.420123), and Microchip Technology (H = 0.398787). These equities exhibit a propensity to return to their long-term average values following deviations. This indicates that the price fluctuations of these assets contradict the premise of efficient markets following a random walk pattern, and may exhibit a certain degree of predictability.

Regarding Mixed or Near-Efficient Market Behavioreveral, in table 2 several stocks exhibit a pattern where they fluctuate about the confidence interval border, displaying a combination of random walk with modest inclinations towards either persistence or mean-reversio. Qualcomm has a H value of 0.470181, Synopsys has a H value of 0.469303, Cadence Design Systems has a H value of 0.463975, Marvell Technology has a H value of 0.494436, STMicroelectronics has a H value of 0.488768, Teradyne has a H value of 0.487309, Entegris has a H value of 0.477196, Monolithic Power Systems has a H value of 0.459916, and Universal Display Corporation has a H value of 0.435780. The Hurst exponents of these stocks indicate that, although they generally follow market efficiency, there are infrequent instances of minor predictability, suggesting moments of inefficiency.

To summarise, the examination of the Hurst exponents for SMGB.L and its constituent stocks uncovers a range of patterns. Although certain stocks and the ETF demonstrate market efficiency, others display periods of inefficiency marked by mean-reversion. The presence of this variety indicates that the semiconductor business does not consistently conform to the Efficient Market Hypothesis at all times.

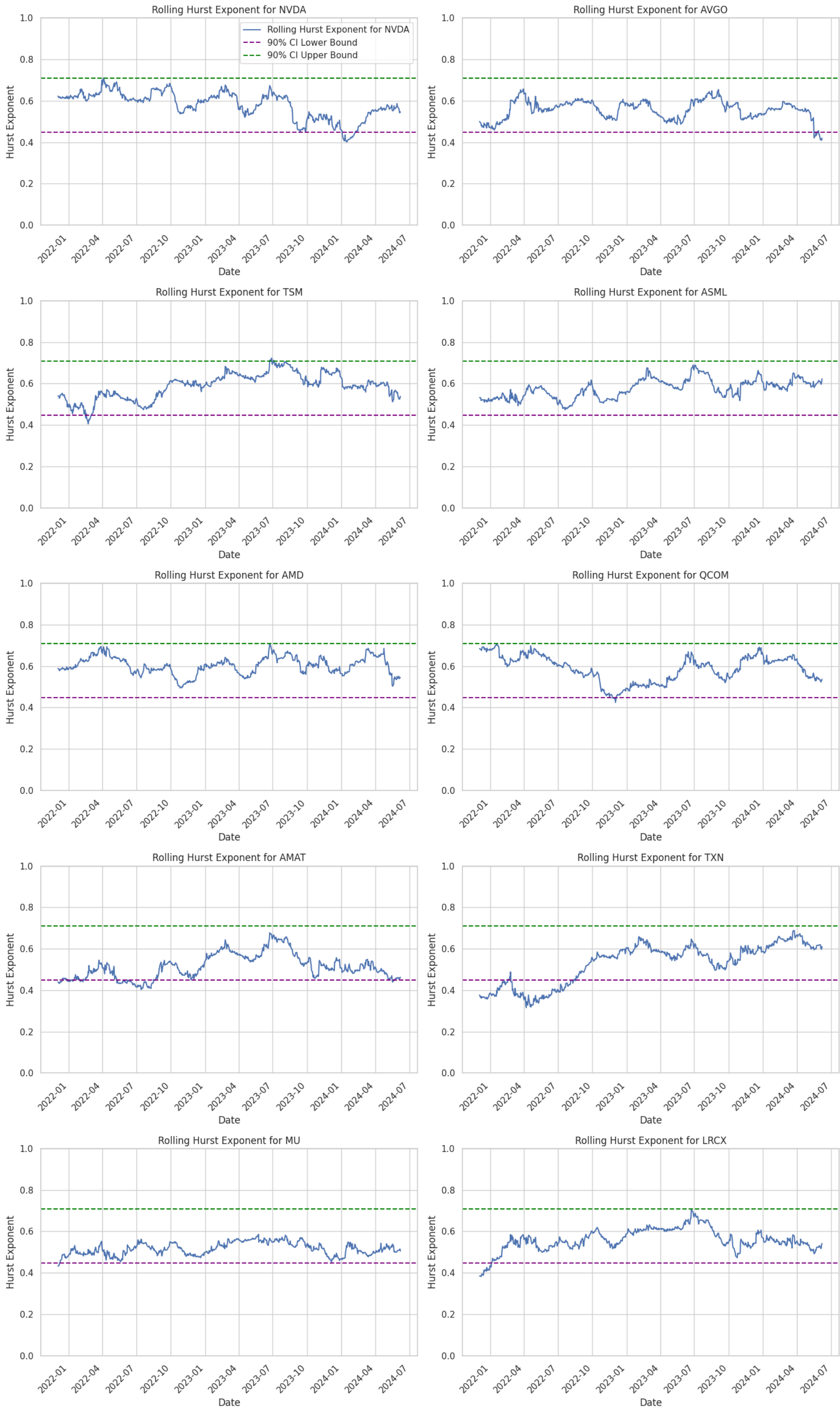
5.2. Rolling Window analysis

Figure 7. Evolution of the Hurst coefficient of the ETF



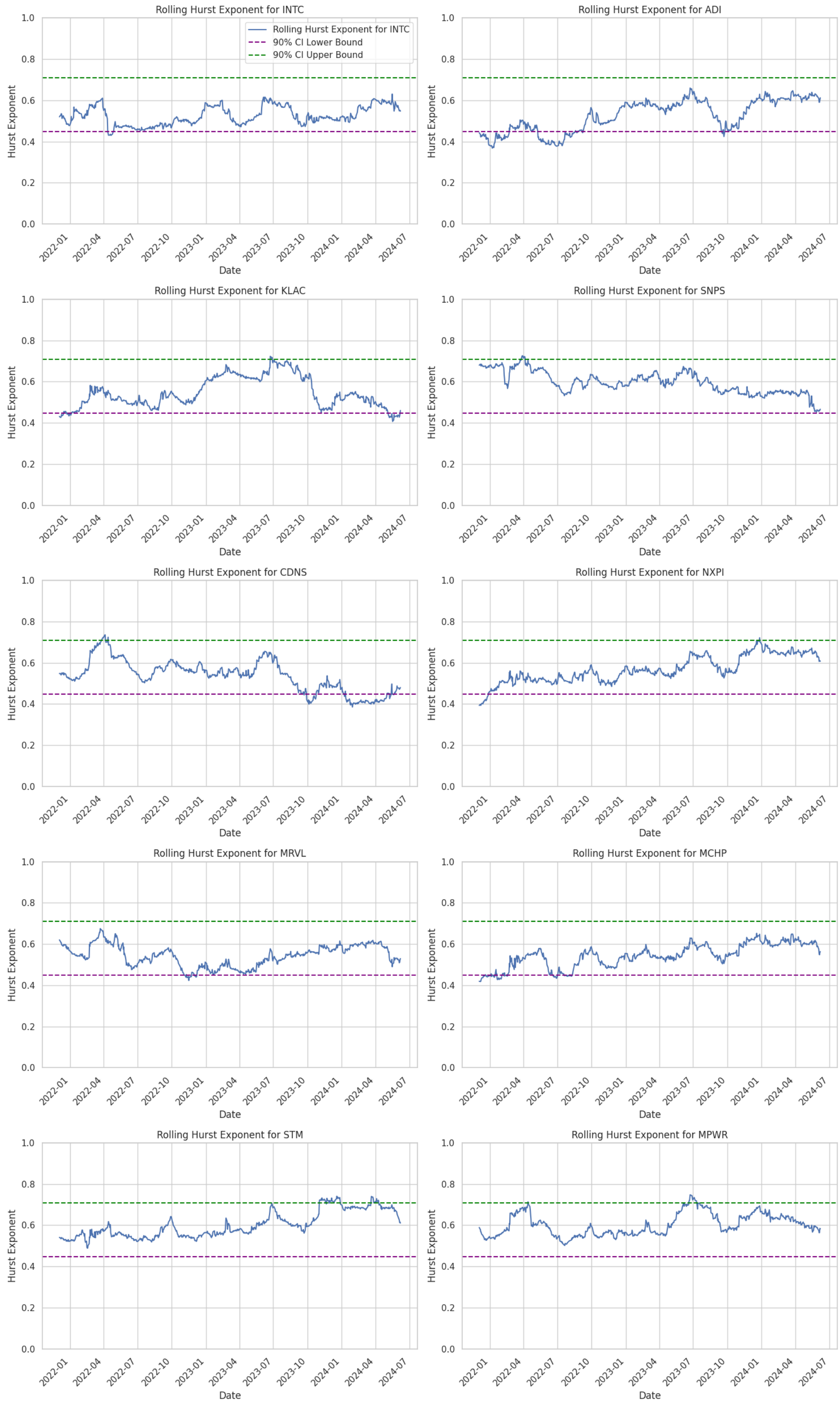
Source: Own elaboration based on the Results of the Analysis.

Figure 8. Evolution of the Hurst coefficient of the components: NVDA, AVGO, TSM, ASML, AMD, QCOM, AMAT, TXN, MU, and LRCX.



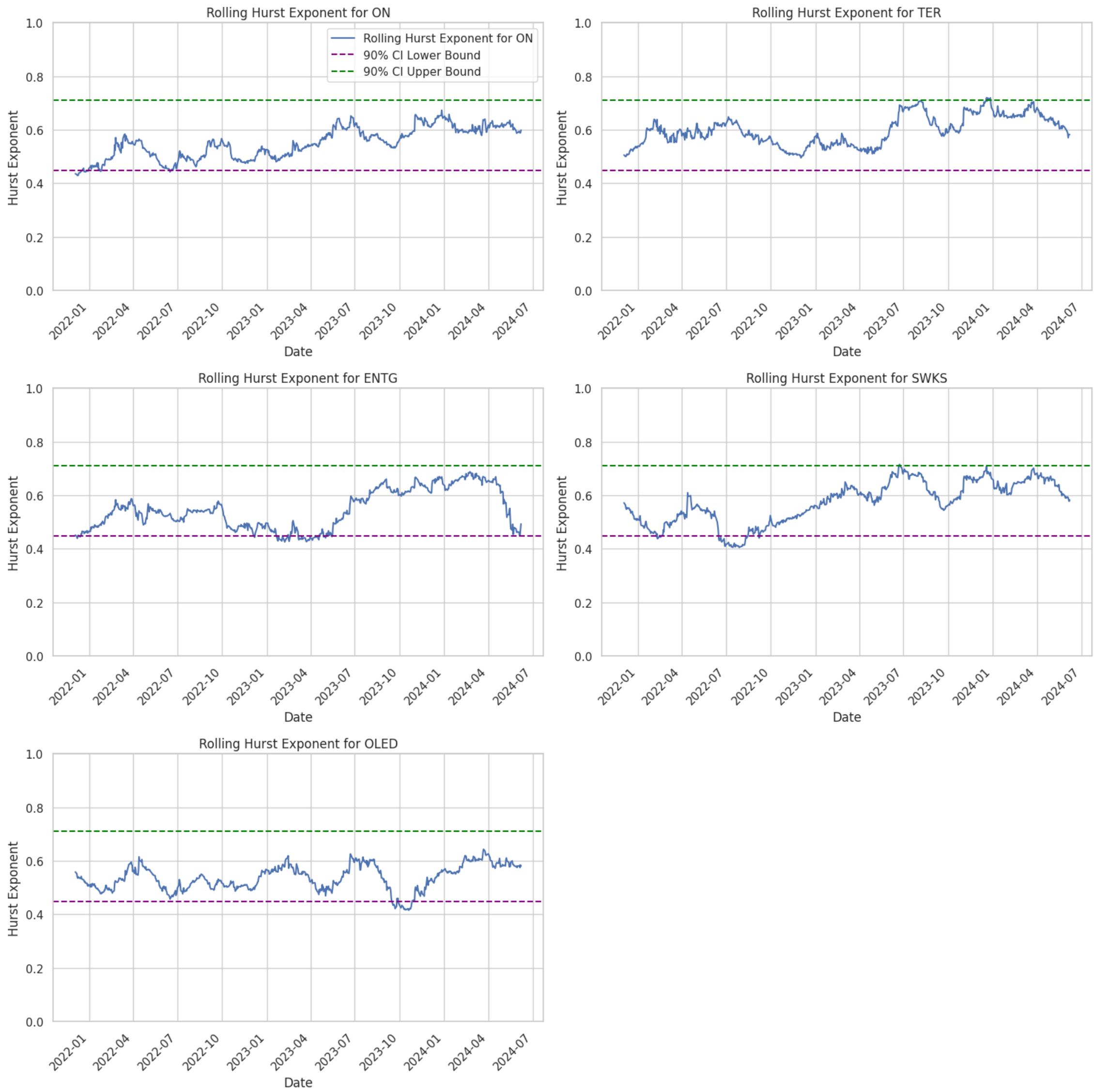
Source: Own elaboration based on the Results of the Analysis.

Figure 9. Evolution of the Hurst coefficient of the components: INTC, ADI, KLAC, SNPS, CDNS, NXPI, MRVL, MCHP, STM, and MPWR.



Source: Own elaboration based on the Results of the Analysis.

Figure 10. Evolution of the Hurst coefficient of the components: ON, TER, ENTG, SWKS, OLED.



Source: Own elaboration based on the Results of the Analysis.

The rolling window study provides a dynamic perspective on the Hurst exponents for SMGB.L and its constituent stocks, demonstrating the evolution of their fractal properties and market behaviours over time as exhibit in Figures 7, 8, 9 and 10. Gaining this perspective is crucial for comprehending the way these assets react to fluctuations in market circumstances and external influences, hence offering more profound insights into their compatibility with the Efficient Market Hypothesis .

SMGB.L (ETF): The rolling Hurst exponent for SMGB.L shows fluctuations around the 0.5 level, suggesting the presence of both trend-following and mean-reversion periods.

These oscillations indicate that although the ETF usually follows market efficiency, it also goes through periods where it deviates from a completely random pattern. The behaviour is governed by the collective dynamics of the stocks that form its foundation.

NVIDIA, ASML Holding, and Advanced Micro Devices frequently have Hurst values that are closer to the upper limit of the confidence interval, suggesting a tendency to follow trends under certain market situations. These trends may be influenced by long-lasting investor sentiment or technological developments in the semiconductor industry.
In contrast, Intel, Analogue Devices, and Texas Instruments often have Hurst values that are either close to or below the lower limit of the confidence interval, suggesting a tendency to return to the mean. These equities have a tendency to return to their average prices over the long run after deviating, especially during economic downturns or periods of market correction.
During the analysis period, certain equities, including Broadcom and Applied Materials, constantly exhibit behaviour that closely aligns with the random walk threshold. This stability indicates that these equities typically conform to the Efficient Market Hypothesis, with price fluctuations staying mostly unpredictable and in line with market efficiency.

6. Conclusions

6.1. Conclusions

This study utilises fractal analysis to evaluate the market efficiency of the semiconductor business, specifically focussing on the VanEck Semiconductor UCITS ETF (SMGB.L) and its constituent companies. By utilising the Hurst exponent, we investigate whether these assets demonstrate behaviour that aligns with the Efficient Market Hypothesis .

The analysis indicates that SMGB.L and its component stocks exhibit a variety of behaviours, ranging from mean-reversion to random walk and near-random walks. Multiple stocks, including NVIDIA, ASML Holding, and Advanced Micro Devices, are categorised within the CI, indicating a correlation with market efficiency. This indicates that the price movements of these assets are mostly unpredictable and adhere to the criteria of the Efficient Market Hypothesis as desribed by Fama (1970, 1991). Conversely, equities such as Texas Instruments, Analogue Devices, and Microchip Technology have mean-reverting trends, suggesting deviations from the random walk nature of efficient markets. These indicate periods of inefficiency in which price swings are somewhat predictable as they tend to return to a long-term average.

The analysis of rolling windows offers additional understanding of the ever-changing characteristics of these behaviours, demonstrating the temporal variations in the Hurst exponents for SMGB.L and its constituent elements. This dynamic perspective illustrates the assets' responsiveness to fluctuating market conditions and external events, encompassing periods of both effectiveness and ineffectiveness.

In summary, the results indicate that although the semiconductor sector often demonstrates market efficiency in line with the Efficient Market Hypothesis , there are also notable instances of deviations from this pattern. These deviations indicate periods when the market is not completely efficient, influenced by mean-reverting behaviour. Investors and analysts rely on these insights to comprehend the fractal characteristics of semiconductor companies and enhance their investing strategies in this continually changing sector.

6.2. Possible future remarks

Subsequent investigations can extend the results of this work by improving the multifractal analysis and investigating novel approaches. Several avenues for future research include:

- Enhanced Multifractal Analysis: Expanding the analysis to include higher-order moments and supplementary fractal metrics should yield a more profound comprehension of the multifractal characteristics across different economic circumstances. By doing so, a more detailed examination of the multifractality and its consequences for financial time series can be conducted.
- Dynamic clustering approaches involve the implementation of methodologies that can adapt to changing market conditions. By using these approaches, we can gain insights on the evolution of fractal behaviours of financial assets over time. These approaches could be especially valuable in comprehending the effects of sudden market disruptions and long-term patterns on the grouping of assets.
- Comparative Sector Analysis: By comparing the fractal and clustering characteristics of the semiconductor sector with those of other sectors, we may gain a more comprehensive understanding of sector-specific behaviours. This analysis could aid in the identification of distinct fractal characteristics and their impact on investing strategies in various market sectors.
- Machine learning integration: Combining fractal measurements with machine learning models has the potential to improve prediction powers in financial markets. Investigating the potential application of these indicators to enhance the effectiveness of trading algorithms and risk management systems holds promise for future research.

Declaración de Uso de Herramientas de Inteligencia Artificial Generativa en Trabajos Fin de Grado

ADVERTENCIA: Desde la Universidad consideramos que ChatGPT u otras herramientas similares son herramientas muy útiles en la vida académica, aunque su uso queda siempre bajo la responsabilidad del alumno, puesto que las respuestas que proporciona pueden no ser veraces. En este sentido, NO está permitido su uso en la elaboración del Trabajo fin de Grado para generar código porque estas herramientas no son fiables en esa tarea. Aunque el código funcione, no hay garantías de que metodológicamente sea correcto, y es altamente probable que no lo sea.

Por la presente, yo, [Nombre completo del estudiante], estudiante de [nombre del título] de la Universidad Pontificia Comillas al presentar mi Trabajo Fin de Grado titulado "[Título del trabajo]", declaro que he utilizado la herramienta de Inteligencia Artificial Generativa ChatGPT u otras similares de IAG de código sólo en el contexto de las actividades descritas a continuación [el alumno debe mantener solo aquellas en las que se ha usado ChatGPT o similares y borrar el resto. Si no se ha usado ninguna, borrar todas y escribir "no he usado ninguna"]:

1. **Interpretador de código:** Para realizar análisis de datos preliminares.
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3. **Corrector de estilo literario y de lenguaje:** Para mejorar la calidad lingüística y estilística del texto.
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Afirmo que toda la información y contenido presentados en este trabajo son producto de mi investigación y esfuerzo individual, excepto donde se ha indicado lo contrario y se han dado los créditos correspondientes (he incluido las referencias adecuadas en el TFG y he explicitado para que se ha usado ChatGPT u otras herramientas similares). Soy consciente de las implicaciones académicas y éticas de presentar un trabajo no original y acepto las consecuencias de cualquier violación a esta declaración.

Fecha: 21 de Junio

Firma: ___________________________

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8. Appendix

8.1. Python Code for Fractal Analysis

```
import pandas as pd
import numpy as np
import yfinance as yf
import matplotlib.pyplot as plt
import seaborn as sns

def download_data(tickers, start_date, end_date):
    data = yf.download(tickers, start=start_date, end=end_date)['Adj Close']
    return data

def log_returns(data):
    return np.log(data / data.shift(1)).dropna()

def generate_gaussian_white_noise(length, mu=0, sigma=1):
    return np.random.normal(mu, sigma, length)

def calculate_hurst_exponent(data, min_lag=10):
```

```
    n = len(data)
    max_lag = n // 2
    lags = range(min_lag, max_lag)
    rs = []
    valid_lags = []
    for lag in lags:
        segment_means = [data[i:i + lag].mean() for i in range(0, n, lag)]
        segment_rescaled_ranges = []
        for i in range(0, n, lag):
            segment = data[i:i + lag]
            if len(segment) < lag:
                continue
            mean_adjusted = segment - segment.mean()
            cumulative_deviation = np.cumsum(mean_adjusted)
            r = cumulative_deviation.max() - cumulative_deviation.min()
            s = segment.std(ddof=1)
            if s != 0:
                segment_rescaled_ranges.append(r / s)
        if segment_rescaled_ranges:
            rs.append(np.mean(segment_rescaled_ranges))
            valid_lags.append(lag)
    if len(valid_lags) > 0 and len(rs) > 0:
        rs_log = np.log10(rs)
        lags_log = np.log10(valid_lags)
        slope, intercept = np.polyfit(lags_log, rs_log, 1)
        hurst_exponent = slope
    else:
        hurst_exponent = np.nan
    return hurst_exponent

def generate_and_calculate_ci(length, num_series=10000):
    synthetic_hursts = []
    for _ in range(num_series):
        synthetic_series = generate_gaussian_white_noise(length)
```

```
        hurst = calculate_hurst_exponent(synthetic_series)
        synthetic_hursts.append(hurst)
    ci_lower = np.percentile(synthetic_hursts, 5)
    ci_upper = np.percentile(synthetic_hursts, 95)
    return ci_lower, ci_upper

def generate_and_calculate_ci_rolling(length, num_series=10000):
    synthetic_hursts = []
    for _ in range(num_series):
        synthetic_series = generate_gaussian_white_noise(length)
        hurst = calculate_hurst_exponent(synthetic_series)
        synthetic_hursts.append(hurst)
    ci_lower_rolling = np.percentile(synthetic_hursts, 5)
    ci_upper_rolling = np.percentile(synthetic_hursts, 95)
    return ci_lower_rolling, ci_upper_rolling

def calculate_rolling_hurst(data, window_size, step_size, min_lag=10):
    rolling_hurst = []
    rolling_dates = []
    for start in range(0, len(data) - window_size + 1, step_size):
        window_data = data[start:start + window_size]
        hurst_exponent = calculate_hurst_exponent(window_data)
        rolling_hurst.append(hurst_exponent)
        rolling_dates.append(price_data.index[start + window_size - 1])
    return rolling_dates, rolling_hurst

start_date = "2020-12-11"
end_date = "2024-06-11"
etf_ticker = "SMGB.L"
components_tickers = [
    "NVDA", "AVGO", "TSM", "ASML", "AMD", "QCOM", "AMAT", "TXN", "MU",
    "LRCX", "INTC", "ADI", "KLAC", "SNPS", "CDNS", "NXPI", "MRVL", "MCHP",
    "STM", "MPWR", "ON", "TER", "ENTG", "SWKS", "OLED"
]
```

```
all_tickers = [etf_ticker] + components_tickers
price_data = download_data(all_tickers, start_date, end_date)
price_data = price_data.interpolate(method='linear')
log_rets_data = log_returns(price_data)
max_observations = max(len(log_rets_data[ticker].dropna()) for ticker in all_tickers)
ci_full_lower, ci_full_upper = generate_and_calculate_ci(max_observations,
num_series=10000)
print(f'90% CI for Random Walk Hurst Exponent (Full Period): [{ci_full_lower:.4f},
{ci_full_upper:.4f}]')
max_observations = 252
ci_full_lower_rolling, ci_full_upper_rolling =
generate_and_calculate_ci_rolling(max_observations, num_series=10000)
print(f'90% CI for Random Walk Hurst Exponent (Full Period):
[{ci_full_lower_rolling:.4f}, {ci_full_upper_rolling:.4f}]')
hurst_exponents = {}
observations_count = {}
print(f"Calculating Hurst Exponent for {etf_ticker}")
hurst_etf = calculate_hurst_exponent(log_rets_data[etf_ticker].dropna().values.flatten())
hurst_exponents[etf_ticker] = hurst_etf
observations_count[etf_ticker] = len(log_rets_data[etf_ticker].dropna())
print(f'Hurst Exponent for {etf_ticker}: {hurst_etf:.4f}')
for ticker in components_tickers:
    log_rets = log_rets_data[ticker].dropna()
    hurst_exponent = calculate_hurst_exponent(log_rets.values.flatten())
    hurst_exponents[ticker] = hurst_exponent
    observations_count[ticker] = len(log_rets)
    print(f'Hurst Exponent for {ticker}: {hurst_exponent:.4f}')
hurst_summary_df = pd.DataFrame({
    'Ticker': [etf_ticker] + components_tickers,
    'Hurst Exponent': [hurst_exponents[ticker] for ticker in [etf_ticker] +
components_tickers],
    'Number of Observations': [observations_count[ticker] for ticker in [etf_ticker] +
components_tickers]
})
```

```
print(hurst_summary_df)
hurst_summary_df.to_csv("hurst_summary_results.csv", index=False)
plt.figure(figsize=(14, 8))
colors = []
for hurst in hurst_summary_df['Hurst Exponent']:
    if hurst > ci_full_upper:
        colors.append('green')
    elif hurst < ci_full_lower:
        colors.append('red')
    else:
        colors.append('dodgerblue')
scatter = plt.scatter(hurst_summary_df['Ticker'], hurst_summary_df['Hurst Exponent'], c=colors, s=200)
plt.axhline(ci_full_lower, color='purple', linestyle='--', label=f'90% CI Lower Bound = {ci_full_lower:.4f}')
plt.axhline(ci_full_upper, color='green', linestyle='--', label=f'90% CI Upper Bound = {ci_full_upper:.4f}')
plt.ylim(0, 1)
plt.title('Hurst Exponent for Each Ticker')
plt.xlabel('Ticker')
plt.ylabel('Hurst Exponent')
plt.xticks(rotation=90)
legend_elements = [
    plt.Line2D([0], [0], marker='o', color='w', label='Hurst Exponent', markerfacecolor='dodgerblue', markersize=10),
    plt.Line2D([0], [0], marker='o', color='w', label='Antipersistent (red dot)', markerfacecolor='red', markersize=10),
    plt.Line2D([0], [0], color='purple', linestyle='--', lw=2, label=f'90% CI Lower Bound = {ci_full_lower:.4f}'),
    plt.Line2D([0], [0], color='green', linestyle='--', lw=2, label=f'90% CI Upper Bound = {ci_full_upper:.4f}')
]
plt.legend(handles=legend_elements, loc='upper right')
plt.tight_layout()
```

```
plt.grid(True)
plt.savefig("hurst_exponent_results_with_ci_updated.png")
plt.show()
import matplotlib.pyplot as plt
import seaborn as sns
window_size = 252
step_size = 1
sns.set(style="whitegrid")
def plot_rolling_hurst_subplots(tickers, num_columns=2):
    num_tickers = len(tickers)
    num_rows = (num_tickers + num_columns - 1) // num_columns
    fig, axes = plt.subplots(num_rows, num_columns, figsize=(15, num_rows * 5))
    for i, ticker in enumerate(tickers):
        row = i // num_columns
        col = i % num_columns
        ax = axes[row, col] if num_rows > 1 else axes[col]
        rolling_dates, rolling_hurst = calculate_rolling_hurst(log_rets_data[ticker].dropna().values.flatten(), window_size, step_size)
        ax.plot(rolling_dates, rolling_hurst, label=f'Rolling Hurst Exponent for {ticker}')
        ax.axhline(ci_full_lower_rolling, color='purple', linestyle='--', label='90% CI Lower Bound')
        ax.axhline(ci_full_upper_rolling, color='green', linestyle='--', label='90% CI Upper Bound')
        ax.set_ylim(0, 1)
        ax.set_title(f'Rolling Hurst Exponent for {ticker}')
        ax.set_xlabel('Date')
        ax.set_ylabel('Hurst Exponent')
        ax.grid(True)
        ax.xaxis.set_major_formatter(plt.matplotlib.dates.DateFormatter('%Y-%m'))
        plt.setp(ax.get_xticklabels(), rotation=45, ha='right')
        if row == 0 and col == 0:
            ax.legend(loc='upper right')
    for j in range(i + 1, num_rows * num_columns):
```

```
        fig.delaxes(axes.flat[j])
    plt.tight_layout()
    plt.savefig(f"rolling_hurst_group_{'_'.join(tickers)}.png")
    plt.show()

plt.figure(figsize=(14, 8))
rolling_dates, rolling_hurst = calculate_rolling_hurst(log_rets_data[etf_ticker].dropna().values.flatten(), window_size, step_size)
plt.plot(rolling_dates, rolling_hurst, label=f'Rolling Hurst Exponent for {etf_ticker}', color='blue')
plt.axhline(ci_full_lower_rolling, color='purple', linestyle='--', label=f'90% CI Lower Bound = {ci_full_lower_rolling:.4f}')
plt.axhline(ci_full_upper_rolling, color='green', linestyle='--', label=f'90% CI Upper Bound = {ci_full_upper_rolling:.4f}')
plt.ylim(0, 1)
plt.title(f'Rolling Hurst Exponent for {etf_ticker}')
plt.xlabel('Date')
plt.ylabel('Hurst Exponent')
plt.legend(loc='upper right')
plt.grid(True)
plt.gca().xaxis.set_major_formatter(plt.matplotlib.dates.DateFormatter('%Y-%m'))
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.savefig(f"rolling_hurst_{etf_ticker}.png")
plt.show()
num_columns = 2
plot_rolling_hurst_subplots(components_tickers[:10], num_columns=num_columns)
plot_rolling_hurst_subplots(components_tickers[10:20], num_columns=num_columns)
plot_rolling_hurst_subplots(components_tickers[20:], num_columns=num_columns)
```

8.1. Python Code for Sample Descriptives and Time Series

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns

sns.set(style="darkgrid")

plt.figure(figsize=(14, 8))
for ticker in all_tickers:
    plt.plot(price_data.index, price_data[ticker], label=ticker)

plt.title('Adjusted Prices of All Tickers Over Time')
plt.xlabel('Date')
plt.ylabel('Adjusted Price')
plt.legend(loc='best', ncol=2, fontsize='small')
plt.tight_layout()
plt.show()

import pandas as pd
import numpy as np
import yfinance as yf
from scipy.stats import skew, kurtosis, jarque_bera

def download_data(tickers, start_date, end_date):
    data = yf.download(tickers, start=start_date, end=end_date)['Adj Close']
    return data

start_date = "2020-12-11"
end_date = "2024-06-11"

etf_ticker = "SMGB.L"
components_tickers = [
    "NVDA", "AVGO", "TSM", "ASML", "AMD", "QCOM", "AMAT", "TXN", "MU",
    "LRCX", "INTC", "ADI", "KLAC", "SNPS", "CDNS", "NXPI", "MRVL", "MCHP",
    "STM", "MPWR", "ON", "TER", "ENTG", "SWKS", "OLED"
]
```

```
all_tickers = [etf_ticker] + components_tickers
price_data = download_data(all_tickers, start_date, end_date)
price_data = price_data.interpolate(method='linear')

def log_returns(data):
    return np.log(data / data.shift(1)).dropna()

log_rets_data = log_returns(price_data)

stats_list = []

for ticker in all_tickers:
    log_rets = log_rets_data[ticker].dropna()
    mean = log_rets.mean() * 100
    std = log_rets.std() * 100
    max_return = log_rets.max() * 100
    min_return = log_rets.min() * 100
    skewness = skew(log_rets)
    kurt = kurtosis(log_rets)
    jb_test, jb_pvalue = jarque_bera(log_rets)
    stats_list.append({
        'Ticker': ticker,
        'Num. Observ.': len(log_rets),
        'Mean (%)': mean,
        'Std (%)': std,
        'Max (%)': max_return,
        'Min (%)': min_return,
        'Skew': skewness,
        'Kurtosis': kurt,
        'Jarque-Bera test': f"{jb_test:.2f} ({'***' if jb_pvalue < 0.01 else '**' if jb_pvalue <
0.05 else '*' if jb_pvalue < 0.10 else ''})"
    })

stats_df = pd.DataFrame(stats_list)
```

```
stats_df = stats_df.sort_values(by='Ticker').reset_index(drop=True)
print(stats_df)
stats_df.to_csv("descriptive_statistics_log_returns.csv", index=False)
```