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بسم الله الرحمن الرحيم

Dedication

This thesis is dedicated to my family whose support, encouragement, and sacrifices have been the foundation of my academic journey. Every day they have inspired me to strive for excellence and have always believed in my potential.

I also dedicate this work to my mentors, professors, and the instructors who taught me throughout my academic years, from whom I have learned so much and with whom I have shared invaluable moments. To everyone who has supported and influenced me along the way,

I am deeply grateful

Thanks and Gratitude

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Abstract

This study assesses the relative effectiveness of conventional volatility forecasting models against artificial intelligence methodologies within the context of emerging financial markets. Drawing on daily data for the iShares MSCI Emerging Markets ETF (EEM) spanning the period from 2003 to 2024, the research implements econometric models, including GARCH and Value at Risk (VaR), in conjunction with artificial intelligence models such as Long Short-Term Memory (LSTM). The study highlights the inherent structural vulnerabilities and distinct volatility characteristics of emerging markets, while also evaluating model performance across the designated study intervals. The results indicate greater predictive accuracy achieved by the artificial intelligence models, suggesting that these advanced approaches substantially enhance the efficacy of volatility forecasting and risk management practices in emerging market environments.

Keywords: Volatility Forecasting, Risk Management, Emerging Markets, Exchange-Traded Funds (ETFs), GARCH, LSTM, Value at Risk (VaR).

الملخص

تُقيّم هذه الدراسة الفعالية النسبية لنماذج التنبؤ بالتقلبات التقليدية مقابل منهجيات الذكاء الاصطناعي في سياق الأسواق المالية الناشئة. بالاعتماد على بيانات يومية لصندوق المؤشرات المتداولة iShares MSCI للأسواق الناشئة (EEM) الممتدة من عام 2003 إلى عام 2024، يطبق البحث نماذج الاقتصاد القياسي، بما في ذلك نموذج GARCH والقيمة المعرضة للخطر(VaR) ، بالتزامن مع نماذج الذكاء الاصطناعي مثل الذاكرة طويلة قصيرة المدى (LSTM). وتسلط الدراسة الضوء على مواطن الضعف الهيكلية الكامنة وخصائص التقلب المتميزة للأسواق الناشئة، مع تقييم أداء النماذج في الوقت نفسه عبر فترات الدراسة المحددة. وتشير النتائج إلى دقة تنبؤية أكبر تحققها نماذج الذكاء الاصطناعي، مما يوحي بأن هذه المقاربات المتقدمة تُحسّن بشكل كبير من فعالية التنبؤ بالتقلبات وممارسات إدارة المخاطر في بيئات الأسواق الناشئة.

الكلمات المفتاحية : التنبؤ بالتقلبات، إدارة المخاطر، الأسواق الناشئة، صناديق المؤشرات المتداولة (ETFs)، GARCH، LSTM، القيمة المعرضة للخطر (VaR).

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General Introduction

In the last few decades, the shaping power of economic globalization and capital liberalization has created a new class of markets called emerging markets. Emerging markets are hybrids of developing economies and aspirations of industrialized societies. Volatility and challenges define this market, but they also provide an opportunity for investing. Emerging markets are highly susceptible to the whims of global market fluctuations and changing capital flows, due to underdeveloped financial institutions in relation to more mature economies, and the markets' exposure to geopolitical occurrences, commodity price fluctuations, and changing global macroeconomic and central bank policy contexts.

Emerging markets exhibit greater volatility than developed markets due to weaker institutions and the unpredictable patterns of foreign investment inflows. This creates an interesting context for testing the effectiveness of risk management programs and volatility forecasts. Managing this volatility is a priority for both investors and policymakers, as it can limit losses and enhance the effectiveness of outcomes stemming from fiscal and monetary policies. This is particularly important in the context of improving the relative attractiveness of these markets for incoming foreign capital and achieving domestic financial stability (Karanasos, Yfanti, & Hunter, 2022).

Subject to this framework is the importance of Exchange-Traded Funds (ETFs) as a bridge for investor access to frontier markets. ETFs in general, especially those that track indices such as the MSCI Emerging Markets Index, are a great way to assess how emerging markets are performing and to compare the volatility of countries based on their economic strength or lack thereof. One of the most common of these tools is the iShares MSCI Emerging Markets ETF (EEM), which is among the most prominent and actively traded ETFs. It provides a representative snapshot of a broad basket of stocks listed in various emerging markets such as Brazil, India, South Africa, China, and Mexico, and is frequently used as a benchmark in academic studies and investment analyses.

These markets present fundamental obstacles to risk and volatility management because of their inherent characteristics. Researchers and financial practitioners have developed advanced quantitative models including Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models and Value at Risk (VaR) because these models have become standard tools for volatility forecasting and financial risk measurement. These models gain their value from both statistical accuracy and robust theoretical structure. Financial markets especially emerging markets have experienced rapid changes that require more sophisticated adaptive approaches for volatility forecasting. Artificial Intelligence (AI) techniques lead the way in this transformation because they have transformed financial data analysis and volatility prediction methods (Labde, et al., 2025).

By means of technologies like Machine Learning and Artificial Neural Networks, AI offers outstanding capabilities in handling large and complex datasets and in detecting patterns that traditional models cannot identify. Its superior ability to manage non-linear and time-dependent data makes it a top contender in the development of future risk management tools tailored to the conditions of developing markets.

Therefore, this research seeks to evaluate the performance of conventional volatility forecasting methods against artificial intelligence approaches in emerging financial markets. Particular attention will be given to testing model accuracy and their ability to reduce investment risks through an empirical study using real data from the iShares MSCI Emerging Markets ETF (EEM).

Based on what has been presented, we now present the following key problem, which forms the cornerstone of this research and around which the study will be centered:

How effective are volatility prediction models and traditional risk management tools compared to artificial intelligence techniques in emerging financial markets?

To address the main research problem, this study hypothesizes that: Artificial intelligence (AI) model outperforms traditional models in forecasting volatility and risk management.

The following sub-hypotheses have been formulated:

Sub-hypothesis 1: Emerging equity markets (EEM) tend to be more volatile than developed markets.

Sub-hypothesis 2: ETF returns in emerging equity markets exhibit a high volatility clustering effect.

Sub-hypothesis 3: Traditional risk management tools, such as parametric VaR, are surpassed by models that account for heteroscedasticity.

Sub-hypothesis 4: Artificial intelligence (AI) model outperforms traditional models in forecasting volatility and risk management.

Each of the proposed hypotheses will be addressed in a separate chapter within the structure of this study. To answer the research question, historical daily price data of the iShares MSCI Emerging Markets ETF (EEM) was analyzed. The EEM series was selected due to its broad coverage of numerous emerging markets and the availability of long term historical data, which allows for the evaluation of models across diverse and evolving temporal contexts. Notably, this series has been significantly influenced by major financial crises, including the 2008 Global Financial Crisis, the European Debt Crisis, the 2015 Chinese market turmoil, the COVID-19 pandemic in 2020, and even the Russia-Ukraine war. These events have left clear imprints on market behavior and associated volatility. The inclusion of these periods in the analysis is a critical factor in testing the capability of both traditional and modern models, including artificial intelligence techniques, to forecast volatility under increasing market stress and growing economic uncertainty.

Research Methodology:

Given the scientific and economic nature of this research, the study adopts a positivist approach aimed at measuring observable market realities. A descriptive method is used to present theoretical concepts and prior studies, while the analytical method supports understanding volatility and risk patterns in emerging markets. Finally, the econometric method is applied to compare the performance of traditional models and AI-based techniques using actual financial data from EEM ETF.

In line with academic standards, this study follows the APA (American Psychological Association) referencing style for citation and bibliographic documentation. To maintain clarity and coherence, references have been organized separately for each chapter, ensuring that each chapter stands as an academically self-contained unit with its own set of citations.

Objectives of the Study:

This study aims to explore and analyze key aspects of emerging financial markets by addressing several interrelated objectives. These objectives are designed to provide a comprehensive understanding of market dynamics, risk, and volatility, while evaluating both traditional and modern approaches to forecasting and management.

Study the characteristics of emerging financial markets in terms of volatility levels, market efficiency, and the impact of global economic factors such as financial crises.

Summarize and organize the existing literature on risk and volatility management in emerging financial markets, in order to provide a clearer understanding of these literatures.

Evaluate the effectiveness of traditional models, such as GARCH and VaR, in forecasting volatility and managing risks.

Analyze the performance of artificial intelligence techniques in predicting the volatility of emerging financial markets compared to the traditional models currently used in risk measurement and management.

Importance of the Study:

Understanding the dynamics of emerging financial markets is essential in a rapidly globalizing economy where these markets play an increasingly influential role. This study is significant for several reasons:

Contribution to Market Insight: By shedding light on the behavior and volatility patterns of emerging markets, this research enhances our understanding of their structural complexities, which are often influenced by global economic shocks. Such insights are vital for investors, regulators, and policymakers operating in or engaging with these markets.

Bridging Theory and Practice: The study not only contributes to academic discourse but also provides practical implications by evaluating and contrasting traditional and modern risk forecasting models. This supports better decision-making in risk management and investment strategy.

Advancing Financial Research: Through its comparative analysis of artificial intelligence techniques and traditional models, the study introduces a forward-looking perspective that enriches the existing body of literature and **opens avenues for future research in financial econometrics and AI applications in finance.**

Structure of the Study:

This study is organized into four main chapters, beginning with a preliminary chapter that lays the conceptual groundwork for the research, followed by three core analytical chapters.

The introductory chapter provides meaningful context and defines certain basic terms and concepts for the purpose of the study.It describes in detail the features and general characteristics of emerging markets, Exchange-Traded Funds (ETFs) and their role and structure, the composition and relevance of the MSCI Emerging Markets Index, and the function of the iShares MSCI Emerging Markets ETF (EEM). This chapter provides the conceptual foundation for the empirical and theoretical analyses that follow.

The first chapter is dedicated to the topic of volatility forecasting in emerging markets. Divided into three parts, the chapter begins with a theoretical overview of volatility dynamics and modeling approaches, followed by a review of relevant academic and empirical studies, and concludes with an applied analysis using traditional econometric tools to predict volatility in the EEM ETF.

Chapter Two elaborates on risk management in emerging financial markets. The first section outlines key theoretical foundations and techniques related to financial risk management. The second section reviews prior research on risk assessment in volatile and structurally fragile markets. The third section presents an applied evaluation of risk metrics such as Value at Risk (VaR) and their performance under stress conditions within the context of emerging markets.

The third and final chapter presents a comparative analysis between traditional forecasting and risk management models and those based on artificial intelligence techniques. It begins with an explanation of AI methodologies used in financial modeling. The second section reviews recent empirical contributions that apply AI in volatility and risk prediction. The final section presents the results of the empirical comparison, highlighting how AI models perform relative to conventional models in terms of accuracy, responsiveness, and predictive power.

This organizational structure supports an understanding of volatility and risk management in emerging markets, culminating in a concrete empirical comparison of conventional econometrics-based models and artificial intelligence-based models.

Introductory Chapter : Key Concepts

Chapter Introduction

The dynamics and possibilities of emerging markets are increasingly taking shape and affecting the global economy. Emerging markets are no longer peripheral nations, but have rapid industrialization, high growth, and a shift toward open market economy, as they now serve as engines of trade and investment. Investors wanting to take advantage of their growth will need to know their unique combination of emerging opportunities and corresponding risks.

Despite opportunities and risks associated with these dynamic markets, it is important to keep in mind the unique challenges inherent in investing in emerging economies. These unique challenges, along with inherent risks, include market risk due to volatility, capital repatriation, being information, administration constrained, liquidity, not hedging currency risk, and so forth.

In this combination of opportunity and risk, new financial instruments have captivated investors. One of the most recognizable of these instruments is the Exchange-Traded Fund (ETF). With diversification, liquidity, and, in many cases, lower costs, ETFs provide easier access to a broad range of asset classes, including those in emerging markets

A cornerstone in the construction of many emerging market ETFs is the suite of indices provided by MSCI (Morgan Stanley Capital International). These globally recognized benchmarks serve as the underlying framework for numerous investment products, offering a standardized and widely followed measure of market performance.

A cornerstone in the construction of many emerging market ETFs is the suite of indices provided by MSCI (Morgan Stanley Capital International). These globally recognized benchmarks serve as the underlying framework for numerous investment products, offering a standardized and widely followed measure of market performance.

This chapter will explore the complex universe of emerging markets. First, it will define emerging markets and the key characteristics that define them. Next, it will emphasize the increasing significance of emerging markets in the global economy. It will also address the criteria used to classify them. The chapter will then examine the phenomenon of ETFs as a transformative financial product, including their history, definition, and mechanics. Finally, this chapter will focus on the MSCI Emerging Markets Index, its history, and its importance in the investment world.

1. Emerging markets:

Emerging markets are an integral part of the modern world and its economy, they are unique and present both opportunities for investors. Emerging markets are marked by industrialization, higher economic growth, and moving towards an open market system. Their importance is not merely in the aggregate economic growth, as they are a key player in the trade, investment. However, this dynamic brings with itself certain risks. Understanding emerging markets and how they work is the key to being able to navigate their way through them and take advantage of their growth opportunities.

1.1. Definition Emerging Markets:

Although we all know which economies are emerging market economies, there is no official definition of an emerging market. This is due to the difference in classifications and researchers' perspectives. Therefore, we will mention the most important definitions of emerging markets:

The International Monetary Fund (IMF) defines emerging markets as economies with relatively low to middle income levels that are in the process of industrialization and economic growth. These economies typically display higher growth rates than advanced economies, but they also come with increased volatility and risk (Ruba, 2023).

emerging market economies "are characterized by significant and rapid economic growth evidenced by rising gross domestic product (GDP) in an aggregate and per capita basis, increased trade volumes, as well as increased foreign reserves" (Carrasco & Williams, 2012).

Hoskisson, Eden, Lau, and Wright define an emerging market as "a country that satisfies two criteria: a rapid pace of economic development, and government policies favoring liberalization and the adoption of the free-market system." (Rhew, 2014)

emerging markets are those economies rising from relative poverty to relative wealth, through rapid economic growth. They are characterized by increasing GDP, trade, and foreign reserves. Secondly, emerging markets are generally characterized as countries experiencing institutional transition, away from state control and toward economic freedom.

1.2. Characteristics of Emerging Markets:

As we mentioned earlier, emerging markets, also known as developing economies, are countries with high economic growth potential but with some characteristics that distinguish them from developed economies.

Here are some characteristics of emerging markets (CFITeam, Emerging Markets, 2024) :

Market volatility: Market volatility stems from political instability, external price movements, and/or supply-demand shocks due to natural calamities. It exposes investors to the risk of fluctuations in exchange rates, as well as market performance.

Growth and investment potential: Emerging markets are often attractive to foreign investors due to the high return on investment they can provide. In the transition from being an agriculture-based economy to a developed economy, countries often require a large influx of capital from foreign sources due to a shortage of domestic capital.

Using their competitive advantage, such countries focus on exporting low-cost goods to richer nations, which boosts GDP growth, stock prices, and returns for investors.

High rates of economic growth: Governments of emerging markets tend to implement policies that favor industrialization and rapid economic growth. Such policies lead to lower unemployment, higher disposable income per capita, higher investments, and better infrastructure. On the other hand, developed countries, such as the USA, Germany, and Japan, experience low rates of economic growth due to early industrialization.

Income per capita: Emerging markets usually achieve a low-middle income per capita relative to other countries, due to their dependence on agricultural activities. As the economy pursues industrialization and manufacturing activities, income per capita increases with GDP. Lower average incomes also function as incentives for higher economic growth.

1.3. The importance of emerging markets:

Emerging markets, especially the biggest seven of them (EM7: China, India, Brazil, Russia, Mexico, Indonesia, and Turkey) have recently assumed more important roles in the world economy. They are growing rapidly in their share of world GDP and are introducing new innovations to the global market. The following factors highlight the importance of emerging markets:

Demographic Advantage: Emerging markets typically have large and youthful populations (Ruba, 2023), providing a significant labor force and consumer base that drives domestic demand and attracts foreign investments.

Economic Growth and Global GDP Contribution: Emerging markets, especially China, India, Brazil, and Indonesia have been main engines of global economic development. According to the IMF, emerging markets have been the source of more than 60% of global GDP growth in the last 10 years (2014-2024) (worldeconomics, 2025).

Innovation and Technology Adoption: Many emerging markets are quickly adopting and adapting technological innovations (Ruba, 2023), which can lead to the development of new industries and services, contributing to global technological progress.

Global Integration: Emerging markets have become deeply integrated into the global economy through trade, investment, and financial flows, becoming integral to global supply chains (WorldEconomicOutlook, 2024).

Urbanization and Infrastructure Development: Emerging markets' rapid urbanization is resulting in the development of modern infrastructure and services and create opportunities for different industries and enhance the living standard of citizens (Ruba, 2023).

1.4. Emerging Markets Classification Criteria:

Emerging markets are classified based on a combination of quantitative indicators, such as GDP per capita, market capitalization-to-GDP ratio, and valuation ratios, as well as qualitative factors like the regulatory environment and market accessibility. We will highlight the most important approved classifications (Mardiros & Dicu, 2014) :

Income and Economic Growth Rate: The level of income and the economic growth rate of a country, which are usually represented by the GDP, are very important factors to determine if an economy is emerging or not. These measures capture the economic state and the growth prospects of the market.

Population Size: Large population is a typical feature of emerging markets. Countries with large populations can build their economic development on the number of their people and attract foreign investments.

Geopolitical Influence: Emerging markets are often strategically located from the geopolitical standpoint that may affect their economic decisions and trade relations with other countries.

Foreign Direct Investment (FDI): The degree of foreign direct investment is a key determinant. Emerging markets are usually considered as having high potential for investment because of their large GDP, foreign exchange reserves and relatively low levels of debt.

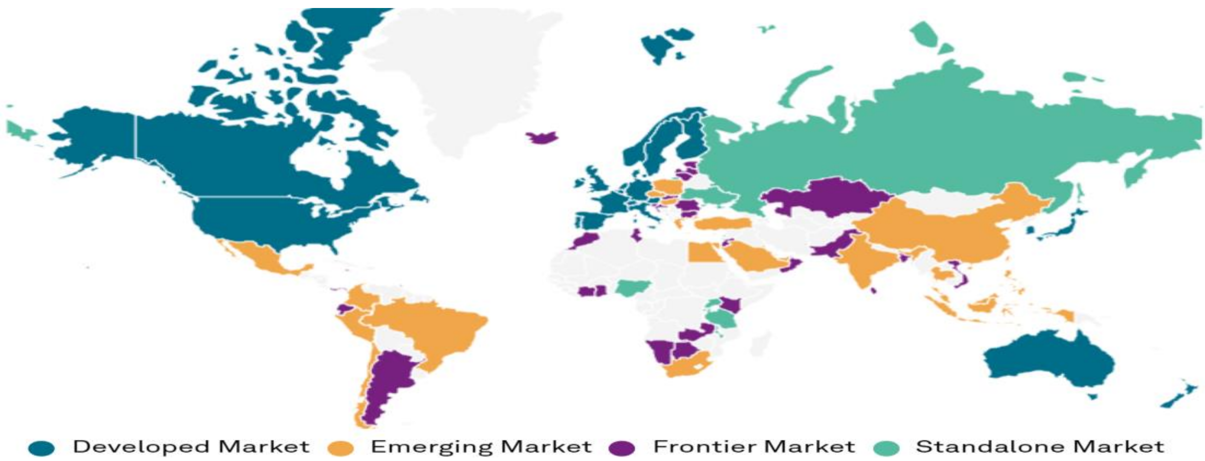
Economic Policies: The implementation of the policies aimed at faster economic growth, the increase in trade and attraction of foreign investments is typical for emerging markets. Many of such policies are aimed at enhancing people's welfare and stability.

ICT Integration: Another criterion is the rate of integration of information and communication technologies (ICT). Countries that incorporate new technologies are likely to increase their productivity and economic development and, therefore, can be regarded as emerging markets.

Standard of Living Improvements: Enhancements in the quality of life, expansion in the size of the middle class, and stability are the characteristics of an emerging market.

Openness to Trade: An environment that allows for the free flow of trade and capital, and is not driven by political factors, is a characteristic of emerging markets. This openness represents the move from dependency to interdependence.

Figure 1: Categorization of Global Markets: A Detailed Listing of Developed, Emerging, Frontier, and Standalone Economies by Region



Developed Markets

Americas	Europe	Mid. East & Africa	Asia Pacific
Canada	Austria	Israel	Australia
United Sates	Belgium		Hong Kong
	Denmark		Japan
	Finland		New Zealand
	France		Singapore
	Germany		South Korea
	Ireland		
	Italy		
	Luxembourg		
	Netherlands		
	Norway		
	Portugal		
	Spain		
	Sweden		
	Switzerland		
	United Kingdom		

Emerging Markets

Americas	Europe	Mid. East & Africa	Asia Pacific
Brazil	Czech Republic	Egypt	China
Chile	Greece	Kuwait	India
Colombia	Hungary	Qatar	Indonesia
Mexico	Poland	Saudi Arabia	Malaysia
Peru	Turkey	South Africa	Philippines
		United Arab Emirates	Taiwan
			Thailand

Frontier Markets

Africa	Americas	Asia	Europe	Middle East
Botswana	Argentina	Bangladesh	Bulgaria	Bahrain
Cote D'Ivoire	Ecuador	Kazakhstan	Croatia	Jordan
Ghana	Jamaica	Pakistan	Cyprus	Oman
Kenya	Panama	Sri Lanka	Estonia	
Mauritius	Trinidad	Vietnam	Iceland	
Morocco			Latvia	
Namibia			Lithuania	
Tunisia			Romania	
Zambia			Slovakia	
			Slovenia	

Standalone Markets

Frontier Markets

Africa		Europe	Middle East
Malawi	Tanzania	Russia	Palestine
Nigeria	Uganda	Ukraine	Lebanon
Rwanda			

Source: (S&PGlobal, 2025)

1.5. Risk Factors in Emerging Markets:

Investing in emerging markets is different from investing in developed markets and has its own set of risks. Through proper analysis and risk response, it is possible for investors to identify and work around the risks that are peculiar to these markets. In this section, we will discuss the risks in the following points (Bouabdallah & Boukessba, 2018):

Volatility: Volatility refers to the degree of deviations in market returns from the estimated returns over a period of twelve months. Economists indicate that a lower degree of volatility is considered a sign of market maturity and advancement. In general, emerging markets tend to be more volatile than most developed markets.

Repatriation of Capital: Despite the openness of emerging markets to foreign investments, they still impose strict restrictions on the inflow and outflow of foreign capital or on the movement of foreign currency. This creates difficulties in transferring funds in and out of the country. Although restrictions on foreign investment have decreased in many markets, a significant number of countries still maintain certain limitations, such as capping the percentage of foreign investment in a given company.

Information and Administrative Costs: The high investment costs in emerging markets compared to developed markets are attributed to elevated expenses related to securities investments, such as brokerage commissions, custody fees, and taxes that may be imposed as a percentage of the total transaction value. Additionally, the lack of adherence to international accounting standards, disclosure requirements, and regulatory rules can lead to what is known as administrative risk.

Liquidity Risk: Liquidity in this context refers to the volume and amount of securities traded on the stock exchange. Higher trading volumes allow investors to acquire desired securities at fair prices and sell them without facing significant price pressure. In emerging markets, a large proportion of listed stocks are not actually available for trading, as they are owned by governments, banks, or families. These major shareholders may refrain from selling their shares to maintain ownership without external shareholders, thereby retaining control over the company's management. This, in turn, affects market liquidity and reduces the supply of tradable securities.

Exchange Rate Risk: An investment portfolio in emerging markets typically includes assets denominated in a foreign currency (the currency of the country in which the investment is made). Consequently, it is exposed to the risk of depreciation in the value of that currency, leading to a decline in the returns generated from investments in that emerging market. Conversely, exchange rate risks can also work in the opposite direction, where an appreciation of the investor’s base currency (the currency of the investment country) results in unexpected returns.

Currency volatility risks are particularly high in many emerging markets due to the lack of economic stability in these countries, especially in the presence of high domestic inflation rates that lead to currency depreciation. As a result, existing foreign investments face potential losses. This was especially evident in Latin America, where unjustifiably high inflation levels were accompanied by continuous depreciation of local currencies against the U.S. dollar and other major currencies. This persistent devaluation led to significant losses for foreign investments in these markets.

Political Risk: This refers to the risks arising from events such as revolutions, military coups, or government interventions in the economy, particularly in capital markets. Such actions are common in many emerging markets and can significantly impact market performance.

2. ETF (Exchange-Traded Fund):

Exchange-Traded Funds (ETFs) are considered one of the most significant financial achievements in recent years. They hold great importance for economic actors, having achieved remarkable and growing success. This is because they provide investors with the benefits of diversification through a single investment product, improved tax efficiency compared to active portfolio management, and lower expenses. Additionally, they can be traded in smaller quantities.

Among the features that have helped make ETFs so appealing are the high degree of transparency in identifying the fund's underlying constituents, intraday valuation, trading speed, as well as the ability to short sell ETFs.

In recent times, ETFs have been highly successful in establishing their presence in the markets in terms of size and diversity. As a result, there is increasing interest from investors, regulators, and academics who seek to assess and understand the implications of this rapid growth.

2.1. History of ETFs:

Depending on how restrictive the authors are in their definition, ETFs as we now know them were first introduced in the early 1990s, either in Canada (with the TIPs that were first traded in 1990) or three years later in the United States (with the SPDRs) (Deville, 2006) .

However, some researchers believe that the first US-listed ETF, the SPDR, was launched by State Street in January 1993 and seeks to track the S&P 500 index. It is still today the largest ETF by far with assets of $178 billion as of September 2017 (Lettau & Madhavan, 2018) .

One of the most notable novel aspects of the first U.S.-listed ETF was that it was introduced on an exchange, allowing investors to trade it all day long like regular equities. The ETF marketplace experienced its effective boom in March 1999 with the launch of the Nasdaq-100 Index Tracking Stock, popularly known as Cubes or Qubes in reference to its initial ticker, QQQ, recently changed to QQQQ. In its second year of trading, a daily average of 70 million shares was being traded in Cubes, which is roughly 4% of the Nasdaq trading volume. The popularity of this specific fund increased market awareness for the other ETFs and the total assets under management more than doubled in 2000, up to $70 billion at the end of December (Frino and Gallagher, 2001). Since then, growth in ETF assets has shown no signs of slowing in the US: 27% in 2001, 23% in 2002, 48% in 2003, 50% in 2004, even remaining high at 31% in 20054. Over the years, ETFs progressively became an alternative to traditional non-traded index mutual funds which led their major competitors such as Vanguard or Fidelity to lower their fees by up to 10 basis points or less.

By the end of 2002, there were 113 ETFs in the US with about $102.14 billion in assets under management. At the end of April 2006, with new cash invested in the existing ETFs and new ETFs based on still more diverse types of indices launched, the ETF marketplace consisted of four stock exchanges listing 216 ETFs with $335 billion in assets. The iShares (sponsored by Barclays Global Investors) and StreetTracks (sponsored by State Street Global Advisors) series present an extremely diversified offer among sectors and/or countries, but ETF assets are dominated by Spider, Cube and Diamond, which are based on relatively broad market indexes (Deville, 2006) .

Exchange-Traded Funds (ETFs) in Europe began in 2000 with their listing on the German and London stock exchanges and quickly expanded to the Stockholm, Euronext, Brussels, Swiss, Helsinki, and Italian exchanges. By 2005, the number of these funds had reached 168, with assets worth $57 billion.

After the global financial crisis, ETFs in Europe experienced massive growth, with total assets rising from $228 billion in 2010 to over $1 trillion at the beginning of the new decade. Despite market declines during the **COVID-19** crisis, assets later recovered, reaching $1.5 trillion by the end of 2021, with 1,926 active funds in Europe (El-Sayed, 2024).

2.2. Definitions of ETFs:

Exchange-traded funds (ETFs) are an investment vehicle that gives investors exposure to underlying markets for stocks, bonds, and other assets, offer portfolio diversification, and access a wide range of investment strategies (IOSCO, 2022) .

Exchange-traded funds (ETFs) are defined as an investment vehicle that is traded throughout the day and aims to replicate the performance of a specific index (El-Sayed, 2024) .

An exchange-traded fund (ETF) is a pooled investment vehicle with shares that trade intraday on stock exchanges at a market-determined price. Investors may buy or sell ETF shares through a broker or in a brokerage account, just as they would the shares of any publicly traded company (ici, 2024).

It can be inferred from the previous definitions that exchange-traded funds (ETFs) are an investment vehicle consisting of a collection of securities that are traded on the stock exchange throughout the day at market prices, and aim to replicate a specific performance, whether actual or synthetic. ETFs offer the possibility of diversifying investors' investments and accessing a wide range of different investment methods.

2.3. Mechanics of ETFs:

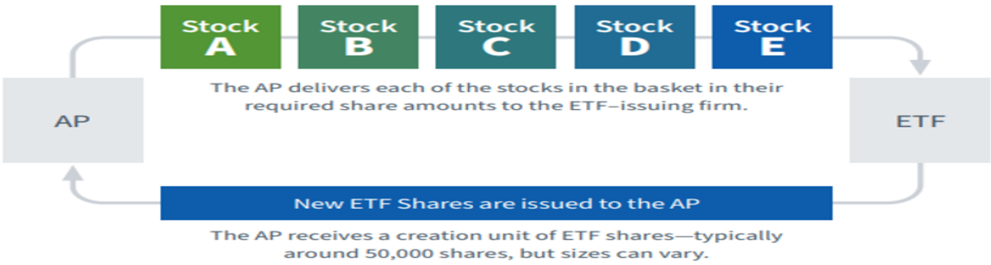
ETFs originate with a fund sponsor, which chooses the ETF’s target index, determines which securities will be included in the “basket” of securities, and decides how many ETF shares will be offered to investors (ICI, 2007) .

ETFs are typically structured as open-ended companies, which allows the number of shares in the fund to vary over time. Unlike managed funds, however, retail and institutional investors must purchase ETF shares on a stock exchange and cannot buy or sell shares directly from the fund. Before an ETF can commence trading, the fund undertakes a process of creation in the primary market (Kosev & Williams, 2011) .

Here’s how this works (WisdomTree, 2025) **:**

- An ETF sponsor decides to create a new fund.
- An authorized participant (AP) purchases the underlying securities then exchanges them for a large block of ETF shares of equal value in what is called an “in-kind” transfer. It is an “in-kind” transaction because the AP is exchanging the same exact securities with the same value, rather than exchanging for cash.
- The block of shares is called a “creation unit” and usually equals between 25,000 and 200,000 shares.
- The AP sells those ETF shares to investors or market makers on an exchange.
- Investors buy and sell ETF shares on the market from other investors, the AP or market makers.

Figure 2: The ETF Creation Process.



Source: (WisdomTree, 2025).

2.4. Type of ETFs:

Funds are usually categorized into two main types based on whether they are physically backed exchange traded funds (ETFs), where these funds actually hold the underlying assets they track and aim to replicate the index's performance. They may well hold all the components of the index or a sample of them. The second type is synthetic exchange traded funds; these funds use derivatives, like swaps, to replicate the index's performance without owning the underlying assets.

These are the most important types of ETFs (Chen J. , 2024) :

Passive ETFs: Passive ETFs aim to replicate the performance of a broader index—either a diversified index such as the S&P 500 or a more targeted sector or trend.

Actively managed ETFs: Do not target an index; portfolio managers make decisions about which securities to buy and sell. Actively managed ETFs have benefits over passive ETFs but charge higher fees.

Bond ETFs: Used to provide regular income to investors. Distribution depends on the performance of underlying bonds which may include government, corporate, and state and local bonds, usually called municipal bonds. Unlike their underlying instruments, bond ETFs do not have a maturity date.

Industry or sector ETFs: A basket of stocks that track a single industry or sector like automotive or energy. The aim is to provide diversified exposure to a single industry, one that includes high performers and new entrants with growth potential. BlackRock's iShares U.S. Technology ETF (IYW), for example, tracks the Russell 1000 Technology RIC 22.5/45 Capped Index.

Commodity ETFs: Invest in commodities like crude oil or gold. Commodity ETFs can diversify a portfolio. Holding shares in a commodity ETF is cheaper than physical possession of the commodity.

Currency ETFs: Track the performance of currency pairs. Currency ETFs can be used to speculate on the exchange rates of currencies based on political and economic developments in a country. Some use them to diversify a portfolio while importers and exporters use them to hedge against volatility in currency markets.

Bitcoin ETFs: The spot Bitcoin ETF was approved by the SEC in 2024. These ETFs expose investors to bitcoin's price moves in their regular brokerage accounts by purchasing and holding bitcoin as the underlying asset. Bitcoin futures ETFs, approved in 2021, use futures contracts traded on the Chicago Mercantile Exchange and track the price movements of bitcoin futures contracts.

Ethereum ETFs: Spot ether ETFs provide a way to invest in ether, the currency native to the Ethereum blockchain, without directly owning the cryptocurrency. In May 2024, the SEC permitted Nasdaq, the Chicago Board Options Exchange, and the NYSE to list ETFs holding ether. And in July 2024, the SEC officially approved nine spot ether ETFs to begin trading on U.S. exchanges.

Inverse ETFs: Earn gains from stock declines without having to short stocks. An inverse ETF uses derivatives to short a stock. Inverse ETFs are exchange-traded notes (ETNs) and not true ETFs. An ETN is a bond that trades like a stock and is backed by an issuer such as a bank.

Leveraged ETFs: A leveraged ETF seeks to return some multiples (e.g., 2× or 3×) on the return of the underlying investments. If the S&P 500 rises 1%, a 2× leveraged S&P 500 ETF will return 2% (and if the index falls by 1%, the ETF would lose 2%). These products use debt and derivatives, such as options or futures contracts, to leverage their returns.

2.5. Advantages and Disadvantages of ETFs:

Exchange-traded funds (ETFs) have become increasingly popular investment vehicles due to their unique blend of features, which combine the benefits of mutual funds and stocks, But it is not without its flaws. These are some of the main advantages and disadvantages:

2.5.1. Advantages of ETFs (Sonigra) :

Diversification: One ETF can give exposure to a group of equities, market segments, or styles. An ETF can track a broader range of stocks or even attempt to mimic the returns of a country or a group of countries.

Trades like a stock: Although the ETF might give the holder the benefits of diversification, it has the trading liquidity of equity.

Lower Fees: ETFs, which are passively managed, have much lower expense ratios compared to actively managed funds, which mutual funds tend to be.

Immediately Reinvested Dividends: The dividends of the companies in an open-ended ETF are reinvested immediately, whereas the exact timing for reinvestment can vary for index mutual funds.

Lower Discount or Premium in Price: There is a lower chance of ETF share prices being higher or lower than their actual value. ETFs trade throughout the day at a price close to the price of the underlying securities, so if the price is significantly higher or lower than the net asset value, arbitrage will bring the price back in line.

2.5.2. Disadvantages of ETFs (Baiden, 2011) :

Market risk: While investment diversification mitigates the effort of a decline in the value of any one security in an ETF portfolio, an ETFs could decline due to larger economic events or policy changes affecting the underlying index.

Narrow based structures: It is estimated that over 90 percent of ETFs are narrow based.

Currency Risk: Fund holdings of international investments may involve risk of capital loss from unfavorable fluctuations in currency exchange rates.

Track Record: Lack of Track Record Investors seeking to invest in ETFs then, may have a very difficult time finding meaningful track records to examine prior to investing in a fund.

Performance Uncertainty: Any ETF sponsor incapable of providing a concrete record of results over a significant period of operations is offering more a promise than a demonstrable business model.

2.6. MSCI Indices and Their Role in ETF Construction:

The MSCI indices are one of the most substantial benchmark indices used by fund managers all over the world. MSCI produces financial indices that span multifarious markets, i.e. developed and emerging markets, as well as multiple sectoral markets. The MSCI Emerging Markets Index is one of the better known indices and captures investment returns for emerging markets, for instance China, India, Brazil, etc. Furthermore, the indices serve as the base indices for developing ETFs as they reflect the performance of the markets they cover and provide investors with the opportunity to indirectly invest in markets.

2.6.1. MSCI Emerging Markets Index: History and Impact:

The MSCI Emerging Markets Index is used to measure the stock market performance within emerging countries. Established in the 1960s, It is one of many indexes created by Morgan Stanley Capital International (MSCI). The index captures mid to large-cap companies across over 12 emerging countries. It also represents over 13% of global capitalization (CFITeam, MSCI Emerging Markets Index, 2025).

Figure 3: MSCI emerging markets daily performance.

Source: (CFITeam, 2025)

Capital International introduced a number of stock indexes in 1965 to mirror the international markets, the first global stock market indexes for markets outside the United States. When Morgan Stanley bought the licensing rights to Capital's data in 1986, it began using the acronym MSCI. In 2004, MSCI acquired Barra, a risk management and portfolio analytics firm, for approximately $816.4 million. After the merger, there was a spin off in an initial public offering (IPO) in 2007, and MSCI began trading on the New York Stock Exchange (NYSE) under the stock ticker MXB. The firm became a fully independent, stand-alone public company from Morgan Stanley in 2009. The firm provides its clients with investment tools including those from Barra and RiskMetrics. It also publishes indexes that are widely available to the investing public (Kenton, 2024).

2.6.2. MSCI global equity indexes:

The MSCI Global Equity Indexes are used by institutional investors worldwide for investment analysis, performance measurement, asset allocation, hedging and the creation of a wide range of index derivatives, funds, ETFs and structured products. From market cap weighted regional, country and sector indexes to indexes based on investment strategies such as factor investing, MSCI delivers The Modern Index Strategy enabling the construction and monitoring of portfolios in a cohesive and complete manner, avoiding benchmark misfit and uncompensated risks (MSCI, 2018).

Figure 4: overview of msci equity indexes.

Source: (MSCI, 2018)

2.6.3. ETFs that track the MSCI Emerging Markets Index:

The MSCI Emerging Markets Index is a key benchmark for large and mid-cap stocks in developing economies. ETFs that track this index offer investors diversified exposure to the growth potential of these markets. Several ETFs are available, each with slightly different characteristics. The following table lists the ETFs that track the MSCI Emerging Markets Index (ETFDatabase, 2025):

Table 1: The following table lists the ETFs that track the MSCI Emerging Markets Index.

Symbol	ETF Name	Total Assets	YTD	Avg Volume	Previous Closing Price	1-Day Change
AVEM	Avantis Emerging Markets Equity ETF	$7,751,930	-1.2%	717,786	$58.10	0.03%
AVSE	Avantis Responsible Emerging Markets Equity ETF	$99,081	-1.5%	10,952	$49.67	0.08%
EEM	iShares MSCI Emerging Markets ETF	$15,834,900	0.2%	29,095,388	$41.91	-0.02%
EJAN	Innovator Emerging Markets Power Buffer ETF January	$104,369	0.1%	28,546	$29.48	0.07%
EJUL	Innovator Emerging Markets Power Buffer ETF - July	$69,685	0.1%	7,335	$24.68	-0.16%
PPEM	Putnam PanAgora ESG Emerging Markets Equity ETF	$40,944	-0.2%	6,495	$20.80	0.19%

Source: (ETFDatabase, 2025)

Chapter conclusion:

In conclusion, this chapter has done the preliminary work for understanding the complex terrain of emerging markets and the growing importance of Exchange-Traded Funds (ETFs) in that context. This chapter has presented definitions of the varied perspectives on emerging markets and explained their unique characteristics and importance as major engines of growth, innovation, and integration in the global economy. It has also analyzed the unique risks present that must be assessed by investors with a long-term interest in exploring these dynamic economies. Next, the chapter discussed ETFs as an innovation in finance with diversified and liquid options for exposure to emerging market opportunities, explaining how they operate, their various typologies, and their respective benefits. Lastly, it illustrated the importance of MSCI indices, namely, the MSCI Emerging Markets Index as the underlying benchmark for many ETFs. This summary establishes a complete base for investigating specific areas of focus regarding emerging market investments and the use of ETFs as one approach to investing in the asset class.

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Chapter One : Volatility Forecasting

Chapter Introduction

Volatility is a huge topic nowadays, and almost anyone with an interest in the financial markets, even remotely, pays particular attention to it. For many in the general public, though, the term simply equates to risk. In contrast, dealers in derivative securities wants to forecast future volatility and correlations of financial asset returns accurately to price the derivatives, optimize asset allocation, apply risk management in portfolio dynamics, and hedge dynamically.

Understanding risks helps individuals avoid unnecessary changes in their plans. Investors' obsession with trying to forecast volatility has led to the creation of numerous models in an attempt to explain the movements in the volatility of financial assets. The best evidence of that is the Global Financial Crisis of 2008, which compelled both practitioners and academics to re-evaluate the structures of our financial models.

The growing volatility in various asset classes calls for a familiarization with the utility of volatility forecasting models, especially during periods of turmoil affecting different sectors of the economy. Despite their almost universal acceptance, present financial models do not function well during extreme market scenarios. Most heavily reliant on historical data, they are often incapable of capturing unprecedented shocks and rapid changes typical of volatile markets. Therefore, considering these models in isolation for real-time market dynamics, external economic shocks, and structural changes often conceals the actual level of risk, misprices derivatives, and obstructs decision-making during exigent situations. And the consequences of mispricing derivatives can indeed be financially significant, both for individuals and large financial institutions alike. When actual market behavior deviates from expectations, the misalignment leads to huge losses.

The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model produced by Tim Bollerslev in 1986 is a fundamental volatility forecasting model.The GARCH model is a built-in model that takes an ARCH model a step further by allowing the conditional variance to depend on past squared residuals as well as its own past values. GARCH models are used in a variety of areas, especially risk management, asset pricing, and financial forecasting due to their ability to capture volatility clustering and time-varying variance.

1.Definition of volatility Forecasting:

Volatility is a complex yet crucial component of financial analysis, enabling investors and risk managers to anticipate market movements. In many cases, volatility is defined as the (instantaneous) standard deviation. However, we will explain some important definitions, namely:

1.1. Definition of volatility:

Volatility in financial markets can be explained as the spread of all likely outcomes of uncertain asset returns. In practice, volatility is generally calculated as the sample standard deviation, which can be calculated as (Vijn, Volatility Forecasting Performance at Multiple Horizons, 2017) :

$$\sigma_t^2 = \frac{1}{T-1}\sum_{t=1}^{T} (r_t - \mu)^2$$

Where: $\boldsymbol{rt}$ denotes the return on day **t** and $\boldsymbol{\mu}$ is the average return over the entire period **T**.

The volatility of a security or a market index is a measure of the dispersion of its returns across their mean. Usually denoted by σ, it is defined as the standard deviation of logarithmic returns observed over fixed time intervals (Emilio & Nicola, 2019/2020):

$$\sigma = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (r_t - \mu)^2}$$

Where:

- $\boldsymbol{r_t} = \ln\left(\frac{S_t}{S_{t-1}}\right)$
- $\boldsymbol{S_t}$ is the price at time t .
- $\boldsymbol{\mu}$ is the mean of r_t .
- $\boldsymbol{n}$ is the number of observations.

1.2. Definition of Forecasting:

Forecasting can be defined as predicting the future development of a particular quantity based on rational methods and current data. Forecasting is of great importance in corporate governance, not only when planning business purchases and processes, but also for strategic management as well as even for risk management in business (Kolkova, 2020).

Forecasting is a technique for making predictions of the direction of future trends based on the analysis of past and present data. Businesses use forecasting to determine how to allocate their budgets or plan for expected expenses for an upcoming period of time (Maiti, 2021).

From the prior definitions, we define volatility forecasting as the prediction of changes in returns of the financial asset that are extremely improbable within a specified time frame. This is achieved by analyzing both historical and current data through the use of different quantitative techniques with the objective of making sensible choices targeting risk management, trading strategies, as well as portfolio management optimization.

2. importance of volatility Forecasting:

Implementing Volatility Forecasting is an important element of financial markets, representing a significant process for risk managers, portfolio managers, and investors. because understanding and predicting market volatility is critical for stakeholders who need to make informed decisions on deal terms when faced with the uncertainties of financial markets. In this section we will highlight the significant role of volatility forecasting (Kambouroudis, 2012):

Accurate volatility forecasting allows risk managers to assess the chances of declines in the portfolios and the potential to implement strategies to avert losses.

Portfolio managers rely on accurate predictions on volatility for their decision-making processes as to whether they want to buy or sell stocks before they become more volatile.

Options traders need volatility forecasting to price the volatility expected to be in existence throughout the life of a contract while taking positions against possible market movements.

Options traders depend on volatility predictions to price expected volatility over the life of a contract and hedge themselves against possible movements in the market.

Market makers use volatility forecasts to set the bid-ask spreads wider in cases of anticipated increased volatility.

3. Challenges in forecasting volatility

Market surprises make volatility forecasting difficult, and traditional models often struggle to adapt to sudden changes caused by external factors such as economic shocks. Traditional forecasting models typically rely on the past experiences and assume that whatever happened in the past will still keep happening in the future These assumptions could be misleading during turbulent times. This section will explore some of the challenges of volatility forecasting (Vijn, 2017) :

Model Performance Discrepancies: Research shows that a variety of advanced volatility models do not always outrun a number of simpler historical models in a variety of situations.

Short-Term vs. Long-Term Forecasting: The performances of temporally oriented techniques could differ fundamentally between short-term and long-term horizons. For instance, while GARCH models may not work adequately for long-term forecasting, simple historical techniques might be satisfactory.

Different Forecast Horizons: Certain methods might respond far better than others depending upon the horizon over which the forecast is made. For example, a method utilizing 1-day-ahead forecasts might not necessarily be appropriate for 1-year-ahead forecasts, adding levels of complexity to model selection.

Loss Functions and Risk: While there is a positive correlation between risk and forecasting horizon, the crux of the issue lies in that longer forecasting is inherently riskier and thereby carries an even greater scope for loss, which is why choosing a loss function becomes very serious business altogether.

Data Limitations: The issues surrounding the proper selection of the time series data, sample periods, and realized volatility proxies complicate the already murky waters associated with comparing forecasting performance across studies.

Volatility clustering: A phenomenon in financial time series is that low volatility is more likely to be followed by low volatility and that one turbulent trading day tends to be followed by another.

Leverage effect: Negative news leads to a fall in the stock price which shifts a firm's debt to equity ratio upwards. The firm has thus increased leverage i.e. higher risk.

Excess kurtosis and skewness: Most financial time series show excess kurtosis skewness. This leads to data that does not follow the normal distribution. Especially fatter left tails and higher peaks are well known features of financial asset returns. The normal distribution has a skewness of zero and a kurtosis of approximately three. Most financial time series are (far) above these values.

Long memory: The autocorrelation of absolute or squared returns declines very slowly which means that volatility is highly persistent and that the effects of volatility shocks decay slowly. research shows that autocorrelation declines even slower for realized volatility.

Weak form market efficiency: Asset returns are usually not autocorrelated. If there exists some autocorrelation, it is only at lag one due to thin trading. In other words, returns are not predictable.

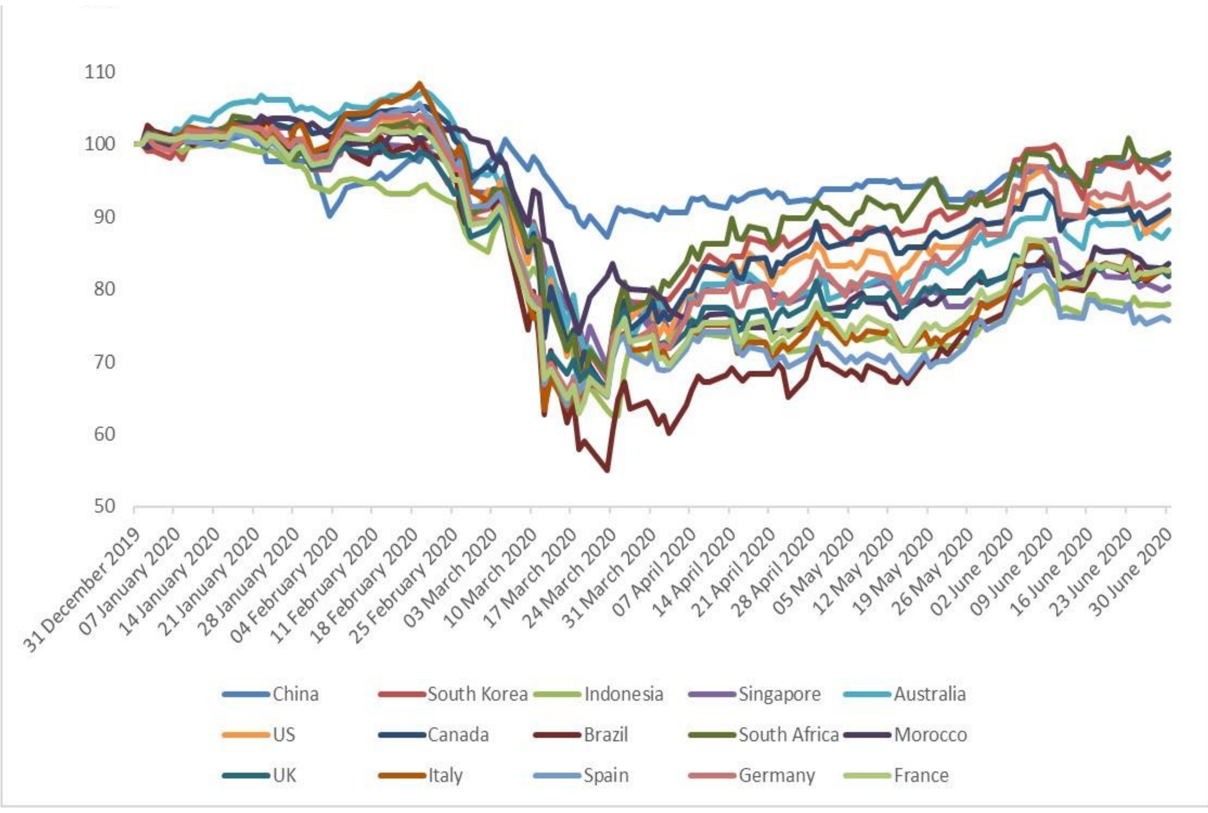
4. Economic and Financial Factors Affecting Volatility:

The volatility of financial markets is influenced by extensive financial, economic, and other aspects which are interconnected and driven by factors such as market sentiment, macroeconomic indicators, geopolitical events, and liquidity conditions. A comprehensive grasp of these elements will help the investors and analysts in making better investment decisions minimizing their risk:

International global happenings, from political upheavals to global economic downturns, can be a driving force behind volatility taking place within local and global markets; Consequently, reactions are generally Heading towards the extremes due to external shocks (Li, Wang, Zhang, & Zhu, Research on the Factors Affecting Stock Price Volatility, 2022). The best case in point of such events is the COVID-19 pandemic. which had a profound effect on equity price volatility, particularly through negative news related to economic conditions (See Figure 1). Another example is the market reaction following Trump's tariff policies, which led to trade wars and turbulence in the stock market (Green, 2025). Global markets experienced a decline of approximately $5 trillion in their market value(See Figure 2) (Jones, 2025).

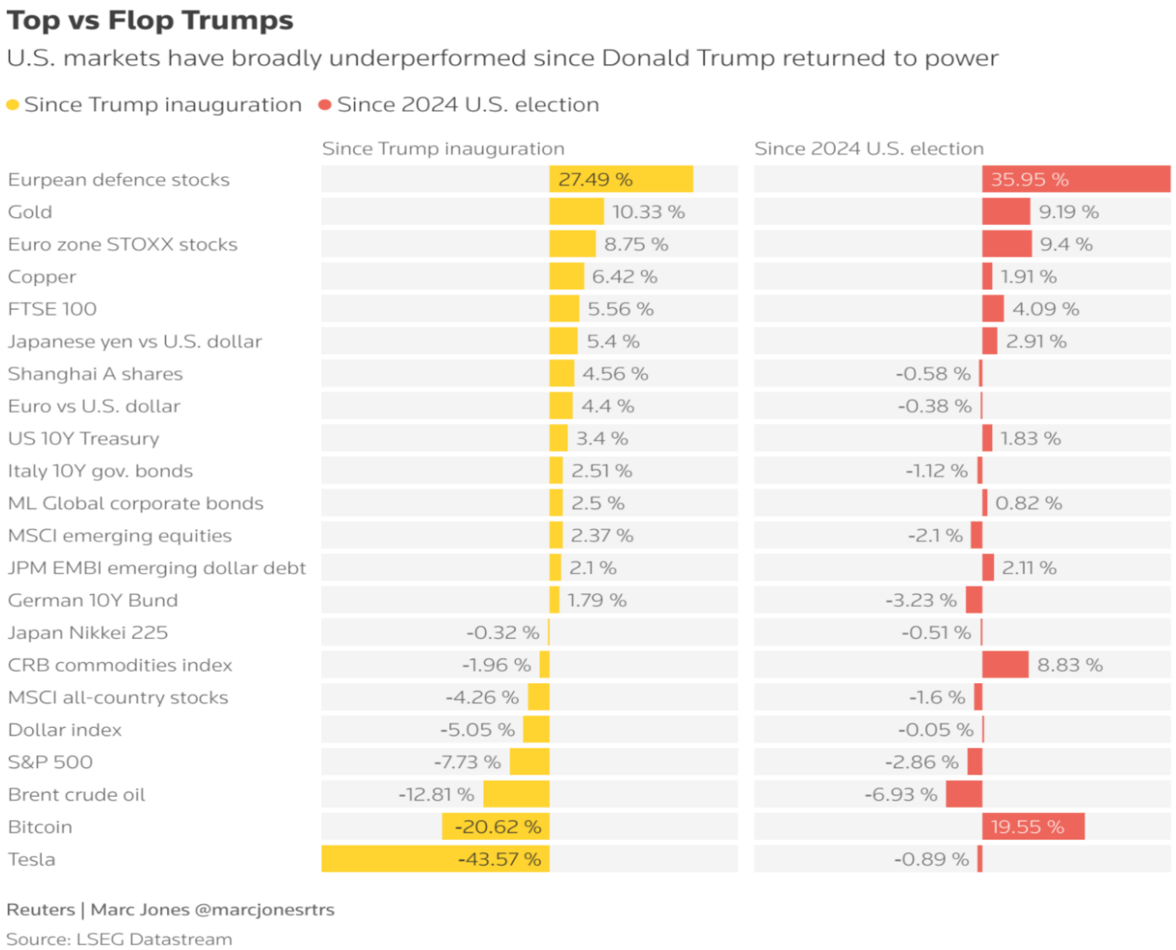
Figure 1: Changes in the stock indices of several countries affected by COVID-19

(December 31, 2019 = 100)



Source: (Kusumahadi & Permana, 2021).

Figure 2: Market Performance Analysis: U.S. and Global Asset Trends Since Donald Trump's Presidencies.



Source: (Jones, 2025).

that a centrally planned economy is intrinsically more volatile than a decentralized market system because the implementation of a centralized plan is likely to generate systemic risks within the economy, thus causing nationwide economic fluctuations. In contrast, good and bad decisions under a decentralized framework tend to neutralize each other and, when disequilibrium occurs in the system, individual agents may quickly adjust their decisions to cope with the situation. (Boqun & Dennis Tao, 2021)

Changes in interest-rate policy deeply affect the stock price and general volatile conditions.The nexus between interest rates and stock market volatility is of utmost importance owing to the subsequent consequence on corporate earnings and investor behavior (Li, Wang, Zhang, & Zhu, 2022). For instance, after the Federal Reserve raised interest rates in 2022, there was high volatility in the stock market due to the investors adjustment of their portfolios amid high borrowing costs.

Investor trading patterns, such as the tendency to sell losing stocks, can also affect volatility. Behavioral finance theories suggest that crowd behavior during market downturns or upturn can lead to increased volatility. (Li, Wang, Zhang, & Zhu, 2022)

The liquidity of stock markets is always influenced by volatility such that any higher volatility would result in the widening of bid-ask spreads, which further brings along high trading costs and that in effect, impacts the confidence of the trader. Besides, the emergence of news about the fundamental value of the asset is the main reason causing changes in market price. Fast incoming news acts to cluster volatility, specifically at high frequencies. (Daly, 2011)

5. Volatility in Emerging vs. Developed Markets:

Variability is considerably different in emerging markets and developed markets because of economic expectations, market development, and vulnerability to risks. Volatility in emerging markets commonly exceeds those of developed markets. Volatility in emerging markets can be attributed to currency fluctuations and relatively low liquidity. Conversely, developed markets are generally more stable because of primary solid financial engines and robust institutional and regulatory structures. Understanding these differences is crucial in the markets:

Differences in Returns and Volatility: The fast-growing developing world often accounts for higher returns relative to developed markets. Studies suggest that while the returns from emerging stock markets can be, in general, higher, they may be much more volatile (Gouveia, 2022). One reason for the increased volatility could be the fact that the emerging economies respond more decisively to information shocks in comparison to the developed economies. Increased sensitivity would further imply that there is a far greater impact of unexpected events on the stock prices in an emerging economy than in a developed economy (Fayyad & Daly , 2010).

Investor Attraction: Some investors prefer emerging markets over developed markets pertaining to the returns on investment but, of course, this comes with a risk. In such volatile markets, there do exist opportunities for considerable gains, especially in times of good economic fortunes. Yet, some of the potential dangers associated with these markets include difficult-to-predict fluctuations and losses that may occur in unfavorable economic conditions (Gouveia, 2022). In simple words, these markets are associated with higher upside potential on an expected basis but simultaneously entail heightened downside risks.

Market Behavior: Developed financial systems usually have lower volatility persistence Due to their more mature financial systems and strong regulatory frameworks, as is the case for the New York Stock Exchange (NYSE) and Euronext. Emerging markets such as National Stock Exchange (NSE) of India and Shanghai Stock Exchange (SSE) of china, on the other hand, are more responsive to international economic activity and capital movements (Gupta, Patni, Sharma, Sharma, & Choubey, 2024).

Table 1: The key aspects of volatility in both EMs and DMs.

Factor	Emerging Markets (EMs)	Developed Markets (DMs)
Economic Stability	More prone to economic shocks and crises	More stable, resilient economies
Political Risk	Higher due to policy uncertainty & governance risks	Lower, with stronger institutions
Market Liquidity	Lower, leading to larger price swings	Higher liquidity, reducing extreme volatility
Exchange Rate Risk	More susceptible to currency fluctuations	Stable currencies with less drastic moves
Capital Flows	More vulnerable to sudden capital outflows	More stable investor confidence

Source: (Gupta, Patni, Sharma, Sharma, & Choubey, 2024).

Literature Review:

The volatility forecast is paramount to the financial industry as it is vital in risk assessment, investment distribution, and derivative market value determination. The capability to foresee changes in market volatility is crucial within a globalized economy. Various attempts have been made to tackle the problem of volatility, including econometric models, such as GARCH, and more advanced algorithms from the field of artificial intelligence and machine learning. In this review of literature, all of the mentioned forecasting techniques will be analyzed for their relevance and efficiency in the context of emerging economies. This forms a basis towards an understanding of how these models cope with a prediction problem of the volatility of these economies.

Emerging markets are characterized by rapid economic growth, a developing financial system, and increasing connections to the global economy. The volatility in these markets can result from a number of issues, including political instability, and shifting patterns of foreign investment. To be true, the efficiencies and peculiarities in structure of such emerging markets do pose unique challenges that warrant robust forecasting methodologies. Enhanced GARCH models, along with hybrid approaches that integrate economic indicators, sentiment analysis, and high-frequency data, have shown promise in improving volatility predictions.

Exchange-traded funds have become very popular in emerging economies, providing investors with diversified exposure to different classes of asset and market segments. Although an ETF is liquid and accessible, it has a tendency to become more volatile because of market sentiment, movements in currency value, and macroeconomic shocks. Hence, the study of volatility forecasting in ETFs in emerging economies is important in creating ways to manage risk and help find market stability. Researchers continuously examine whether ETFs cause markets to be more volatile or less volatile, and therefore an accurate prediction tool is needed to support well-informed investment decision-making. As the ETF market in emerging economies continues to expand, there is an increasing demand for reliable volatility predictors that will also define capital allocation strategies in these parts of the world.

Based on the above, this literature review will examine previous research to identify the theoretical foundations and practical applications of predicting fluctuations in emerging markets. To this end, we hope to point to aspects of the frontier that need to be advanced further in order to advance tools for providing reliable forecasts to the decision makers, both investors and policy makers, who have to navigate these complicated environments.

The study by (Engle, 1982) offers the Autoregressive Conditional Heteroscedasticity (ARCH) model, a novel method that permits the variance to vary through time based on past information. This helps overcome challenges in traditional econometric models that assume constant variance. This study combines the regression model whose disturbances follow an ARCH process, and uses maximum likelihood estimation to estimate the parameters, and a Lagrange multiplier test to test for the ARCH effects. The empirical application is to estimating the variance of UK inflation for the years 1958-1977. The results confirm the ARCH effect, and the variances estimated are notably larger for periods of economic turmoil, especially during the 1970's. The overall study provides evidence that allowing for the variances to vary with time improves accuracy and efficiency in forecasting relative to standard models. The study provides a major contribution to econometric analysis by introducing a new class of stochastic processes to analyze financial and economic time series. The ARCH model is a successful effort that is successfully applied to inflation data provides scope for further analysis of volatility modeling/management and risk assessment.

Building on Engle’s work, subsequent researchers expanded the flexibility of volatility modeling, where (Bollerslev, 1986) expands the framework of the ARCH model by proposing the Generalized

Autoregressive Conditional Heteroskedasticity (GARCH) model, which allows the current variance to depend on past conditional variances of the series. The benefit of generalizing the ARCH model to the GARCH model is the potential for more flexible and efficient modeling of volatility in economic time series. The study provides conditions for wide-sense stationarity and employs maximum likelihood estimation and diagnostic tests to evaluate the model's fit. An application illustrates the use of the GARCH model in a real-world scenario of uncertainty in inflation rates. The results of the study demonstrate that the GARCH model provides a better fit for economic data characterized by time-varying variance than a traditional model characterized by constant variance. The GARCH model also incorporates volatility clustering, a feature of time series data in finance. This contribution to econometric modeling provides a parsimonious yet powerful model effect to capture the effects of both past errors and past variance. The GARCH framework improves the flexibility and precision of modeling volatility for time series analysis and specifically for forecasting of the financial and economic futures.

While the GARCH model provides a robust framework, (Nelson, 1991) addressed the ARCH class of models' limitation about the asymmetric relationship between asset returns and their conditional variance. Building on the basic contribution made by Engle (1982) on ARCH, Nelson's paper provided a better representation of how the volatility in the stock market reacts to prior returns, specifically the finding that Past returns and future volatility exhibit an inverse relationship, as evidenced by the model. Here, he uses the exponential ARCH model, which has a specification incorporating a logarithm that guarantees non-negativity of the conditional variance, to estimate a risk premium model based on daily returns from the CRSP Value-Weighted Market Index from the period 1962 to 1987, correcting for measurement errors in the riskless rates. His results indicated that the exponential ARCH model was able to explain the asymmetric volatility response: A risk premium was found to have a significantly negative relationship with conditional variance, thus supporting earlier studies that found such a connection. This established the model as powerful enough to stress the insight that volatility shoots up during declines in market value and subsides during uptrends, among its important contributions to market dynamics.

Moving beyond stock markets, (Chkili, Hammoudeh, & Nguyen, 2014) analyze the the role of asymmetry and long memory in the modeling and forecasting of the conditional volatility and market risk of four primary commodities: crude oil, natural gas, gold, and silver. The study employs both linear and nonlinear GARCH-type models and assesses value at risk (VaR) for short and long positions during both in-sample and out-of-sample testing. The results reveal that nonlinear GARCH models with long memory and asymmetry features outperform the rest in estimating volatility. In this regard, the FIAPARCH model was found to estimate VaR better than the rest since it caused the least number of breaches to the Basel II rules. This study's strongest aspect is its attempt at estimating long memory and asymmetry volatility for a wide range of commodities. This broader approach increases the relevance of the study for international investors and policymakers that worry about the risks that come with the commodity markets.

Focusing on high-frequency financial data, (Wu, Zhao, Wang, & Han, 2024) studies volatility prediction in the Chinese stock market with high frequency intraday data and current return information using the Real-Time Realized GARCH model. The research relies on out of sample predictions using 5 minute intervals from the SSEC and SZSEC indices conducting loss functions and Model Confidence Set (MCS) tests to measure accuracy. The findings suggest that the Real-Time Realized GARCH model improves both in-sample and out-of-sample volatility forecast accuracy. The inclusion of current return information is important in predicting accuracy and has benevolent effects on portfolio performance, particularly for risk-averse investors employing volatility timing strategies. One of the strong points of this model is that it provides high-frequency and current-return-centric robust volatility modeling framework which is a striking contribution to the literature. It is of practical importance to both investors and policymakers looking for better approaches in managing portfolios and evaluating risks.

Expanding the discussion to a broader perspective, (Poon & Granger, 2003) present a comprehensive survey of volatility forecasting methods appearing in the financial markets, assessing both classical and contemporary ones. All the approaches used in this study include historical volatility, implied volatility methods, and GARCH-type models, which are appraised both in accordance with theoretical considerations and based on empirical analysis across different financial data sets.The results suggest that whereas traditional methods offer fairly reasonable estimates of volatility, GARCH-type models process a reasonable improvement over others for forecasting accuracy. The authors underline the importance of accurate volatility forecasting for risk management and asset pricing. Another important contribution of this paper is to provide above all an exhaustive review of the literature, thus providing a crititcal evaluation of other forecasting methods along with their fairly capitation in making decisions in relation to finance.

Similarly, (Naqvi, Khan, Ghafoor, & Rizvi, 2019) present a study of volatility clustering and the asymmetric behavior of returns in Asian emerging stock markets, examining their implications for the dynamics of financial risk and return. The study includes log-return data from monthly indexes across eight Asian emerging markets between 2009 and 2018. A variety of GARCH models are used in the analysis, including symmetric and asymmetric models such as E-GARCH and GJR-GARCH, in order to evaluate volatility patterns and the influence of news on market fluctuations. The results give evidence for the existence of volatility clustering in all sampled markets, where volatility, being sharpened by negative news, increased much greater than it was in response to positive news. The asymmetric GARCH models appear more capable of capturing those dynamics. A key contribution of this study features its focus on leverage effect, providing insights for the risk-return profile analysis in emerging markets.

In their study, (Rizvi, Naqvi, & Mirza, 2021) focus on the difference between investment of green and grey energy by studying return and volatility spillover between green and grey energy exchange-traded funds (ETFs) and their relationship with traditional finance markets such as stocks and bonds. The analysis considers daily prices from October 2015 to October 2020, and analyzes return spillovers using Vector Autoregression (VAR), volatility spillovers using Multivariate GARCH (BEKK parameterization) model, and impulse response functions with variance decomposition to measure the magnitude and impact of these spillovers. The findings suggest that green energy plays a more prominent role in influencing equity market returns compared to grey energy. Green energy return shocks spill over more strongly to grey energy and equity markets, while grey energy's influence on financial markets appears to be diminishing. However, grey energy continues to significantly affect the bond market, likely through the interest rate channel, and exhibits stronger volatility persistence than green energy. The study's key strength lies in its unique approach of treating green and grey energy as separate asset classes and measuring the spillover effect towards financial markets. This was achieved through the use of ETFs as proxies for market exposure.

Furthermore, (Valadkhani & O'Mahony, 2025) examine the relationship between market broadening, indicated by equal-weighted ETF performance, and future volatility in the U.S. stock market. In analyzing how market broadening, expressed by the S&P 500 Equal Weight ETF (RSP) and the Russell 2000 Equal Weight ETF (IWM), influences volatility, the study employs an EGARCH framework on monthly data ranging from May 2003 to July 2024. The results show that higher market broadening is associated with lower future volatility, thus proving that a higher level of broad market participation contributes to stability. The study also provides additional evidence in favor of an inverted-U hypothesis, where market participation peaked in 2014 and became increasingly concentrated among mega-cap stocks thereafter. An important contribution by this work is that it has macro-level perspective on the behavior of the market linking the dynamics of market broadening with volatility. In doing so, the study provides a helpful tool for practitioners and researchers to gain insights on market conditions without having to delve into more complex individual stock analysis.

China’s financial markets, with their distinct characteristics, have been a focal point for volatility research, In a study published by (Chi, Hao, & Zhang, 2021), the authors evaluated the performance of different volatility models in the volatility of China's SSE50 options market and assessed whether GARCH-type models are more capable than implied volatility in predicting realized volatility going forward and what this would mean for trading strategies. It utilizes a huge dataset of high-frequency spot and options trading data collected from the SSE from August 2017 to September 2020 and implements several ARCH, GARCH, GJR-GARCH, IGARCH, and FIGARCH models. In-sample fit is assessed using log-likelihood and AIC/BIC criteria; out-of-sample forecasting accuracy was analyzed using regression analysis, adjusted R^2, and Mean Absolute Error (MAE). This study also investigates a trading strategy in volatility space based on GARCH forecast volatility and implied volatility. The results showed that the GARCH models and their variants outperform ARCH in the in-sample and out-of-sample tests; they have consistent outperforming capabilities. Contrary to U.S. markets, SSE50 ETFs do not display substantial asymmetric volatility responses to the return histories and therefore indicate that there is no leverage effect. Although IGARCH and FIGARCH model slightly improves forecasting sometimes, GARCH remains preferred due to its simplicity. Besides, the forecasting GARCH volatility levels beat implied volatility at nearly all maturities of options, and a trading strategy exploiting the volatility spread produces significant profit; it reveals inefficiencies in the Chinese options market. The study brings with it several important contributions: it gives new empirical evidence for the volatility behavior in China's infant options market and is the first time it has compared a range of GARCH-type models with the SSE50 options data.

Neural networks have been hybridized with GARCH models to capture volatility dynamics. In this context, (Bildirici & Ersin, 2009) focus on ANN models interfacing with GARCH family models to improve volatility forecasting for the daily returns of the Istanbul Stock Exchange (ISE). Using the daily closing values of the ISE National-100 Index from October 23, 1987 to February 22, 2008, the research employs various GARCH-type models, GARCH, EGARCH, TGARCH, and APGARCH with ANN. The models were evaluated using Root Mean Square Error (RMSE) for accuracy. The results of the study confirm that the ANN-APGARCH model is ameliorative in volatility forecasting beyond the traditional GARCH models. The study also proves strong volatility clustering, asymmetry, and nonlinearity of daily returns, which is complex market behavior that traditional models fail to capture, can easily be captured by ANN. This paper contributes to the literature with the hybrid approach of neural networks with basic framework assuming GARCH structures.

Finally, (Kontsas, 2020) pays attention to the forecasting capabilities and the inherent limitations of the option-implied volatility and the GARCH(1,1) model regarding future volatility in emerging equity markets. The distinct risks facing these markets relative to developed ones are pointed out. With the use of MSCI Emerging Market Price Index data, alongside option data, from January 1, 2015, to December 31, 2019, the forecasting ability was analyzed using Ordinary Least Squares (OLS) regression. This study incorporates loss functions-RMSE and MAE-to assess the fit of the model. The findings reveal that both implied volatility and the GARCH(1,1) model significantly explain future volatility. But, the GARCH(1,1) keeps on outperforming the implied volatility, particularly in daily and monthly forecasts, with the monthly GARCH(1,1) estimates providing the best fit for emerging markets. The paper opens up an important frontier in studying volatility across a number of emerging market economies and highlights the area that has been rather inconclusive in terms of previous findings.

The previous studies can be presented in the following table:

Table 1: Summary of Previous Studies.

Title of the Study	Author(s)	Sample Studied	Study Period	Model Used	Key Findings
Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation	Robert F. Engle (1982)	UK inflation data	1958-II to 1977-II	ARCH model	Introduced the ARCH model, allowing variance to vary over time based on past information. Found significant ARCH effects, with higher variances during economic turmoil, particularly in the 1970s. Demonstrated that modeling time-varying variances improves forecasting accuracy and efficiency.
Generalized Autoregressive Conditional Heteroskedasticity	Tim Bollerslev (1986)	Inflation rate data	1948.2 to 1983.4 (quarterly data)	GARCH model	Proposed the GARCH model, generalizing the ARCH framework to allow current variance to depend on past conditional variances. Demonstrated that the GARCH model provides a better fit for economic data characterized by time-varying variance than traditional models assuming

					constant variance.
Conditional Heteroskedasticity in Asset Returns: A New Approach	Daniel B. Nelson (1991)	Daily returns from the CRSP Value-Weighted Market Index	July 1962-December 1987	Exponential ARCH	Addressed the limitation of ARCH models in capturing asymmetry in volatility. Found that past returns and future volatility exhibit an inverse relationship, with volatility increasing during market declines and decreasing during uptrends.
Volatility forecasting and risk management for commodity markets in the presence of asymmetry and long memory	Walid Chkili, Shawkat Hammoudeh, Duc Khuong Nguyen (2014)	Crude oil, natural gas, gold, and silver prices	January 7, 1997 to March 31, 2011	GARCH, EGARCH, IGARCH, FIGARCH, FIAPARCH, HYGARCH, Risk Metrics	Nonlinear GARCH models with long memory and asymmetry features outperform others in estimating volatility. The FIAPARCH model estimates VaR better, causing the least number of breaches to Basel II rules.
Forecasting Chinese stock market volatility with high-frequency intraday and current return information	Xinyu Wu, An Zhao, Yuyao Wang, Yang Han (2024)	High-frequency intraday data from SSEC and SZSEC indices	January 4, 2005 to December 30, 2022	Real-Time Realized GARCH	The Real-Time Realized GARCH model improves both in-sample and out-of-sample volatility forecast accuracy. Including current return information enhances

					prediction accuracy and benefits portfolio performance, especially for risk-averse investors employing volatility timing strategies.
Forecasting Volatility in Financial Markets: A Review	Ser-Huang Poon, Clive W.J. Granger (2003)	Various financial datasets	Poon and Granger (2003) review papers with various time periods. Not specified	Various models, including GARCH	Traditional methods offer reasonable volatility estimates, but GARCH-type models provide improvements in forecasting accuracy. Accurate volatility forecasting is crucial for risk management and asset pricing.
Evidence of Volatility Clustering and Asymmetric Behavior of Returns in Asian Emerging Stock Markets	Syed M. Waqar Azeem Naqvi, Kanwal Iqbal Khan, Muhammad Mudassar Ghafoor and Syed Kumail Abbas Rizvi (2019)	Monthly index log-return data from eight Asian emerging markets	2009–2018	E-GARCH, GJR-GARCH	Evidence of volatility clustering in all sampled markets. Volatility increases more in response to negative news than positive news. Asymmetric GARCH models better capture these dynamics, providing insights for risk-return profile analysis in emerging markets.

Is green investment different from grey? Return and volatility spillovers between green and grey energy ETFs	Syed Kumail Abbas Rizvi, Bushra Naqvi, Nawazish Mirza (2022)	Daily prices of green and grey energy ETFs, stock and bond indices	October 2015–October 2020	BEKK Multivariate GARCH model, VAR	Green energy has a more significant influence on equity market returns compared to grey energy. Green energy return shocks spill over more strongly to grey energy and equity markets, while grey energy's influence on financial markets is diminishing. Grey energy continues to significantly affect the bond market and exhibits stronger volatility persistence than green energy.
Market broadening and future volatility: A study of Russell 2000 and S&P 500 equal weight ETFs	Abbas Valadkhani, Barry O'Mahony (2025)	S&P 500 Equal Weight ETF (RSP) and Russell 2000 Equal Weight ETF (IWM) data	May 2003–July 2024	EGARCH model	Higher market broadening is associated with lower future volatility, suggesting that broader market participation contributes to stability. Evidence supports an inverted-U hypothesis, with market participation peaking in 2014 and becoming more concentrated among mega-

					cap stocks thereafter.
Volatility model applications in China's SSE50 options market	Yeguang Chi, Wenyan Hao, Yifei Zhang (2022)	Data from the Shanghai Stock Exchange-50 (SSE50) ETF options market	August 8, 2017, to September 30, 2020.	ARCH, GARCH, GJR-GARCH, IGARCH, FIGARCH	GARCH models and their variants outperform ARCH in both in-sample and out-of-sample tests, with consistent superior forecasting capabilities. Contrary to U.S. markets, SSE50 ETFs do not display substantial asymmetric volatility responses to return histories, indicating no leverage effect. GARCH models provide better forecasts than implied volatility, and a trading strategy exploiting the volatility spread produces significant profit, revealing inefficiencies in the Chinese options market.
Improving forecasts of GARCH family models with the artificial neural networks: An application to the daily returns in Istanbul Stock Exchange	Melike Bildirici, Özgür Ömer Ersin (2009)	Daily returns of the Istanbul Stock Exchange (ISE) National-100 Index	October 23, 1987–February 22, 2008	GARCH family models with Artificial Neural Network models (ANN)	The ANN-APGARCH model improves volatility forecasting beyond traditional GARCH models. Captures complex market

					behaviors such as volatility clustering, asymmetry, and nonlinearity that traditional models may fail to capture.
Volatility Forecasting in Emerging Markets	Emma Kontsas (2020)	MSCI Emerging Market Price Index and option data	January 1, 2015 – December 31, 2019	Option implied volatility and GARCH(1,1) model.	Both models significantly explain future volatility, but GARCH(1,1) outperforms implied volatility, especially for daily and monthly forecasts. The best fit for emerging markets is provided by monthly GARCH(1,1) estimates.

The collective contributions of all of these studies demonstrate an improvement in volatility modeling that has progressed from Engle's basic ARCH methodology to more complex hybrid approaches involving artificial intelligence and high-frequency data. As financial markets continue to develop, current models provide a useful framework for managing risk, investment decision making, and forecasting the economy. Future research continues to build models based on the most up-to-date data and methodologies including neural networks, long-memory processes, and real-time analytics to improve forecasting performance and stability within the markets.

Empirical study

Volatility forecasting in financial markets involves modeling and forecasting future changes in asset prices. This allows market participants to quantify their risk exposure, hedge against it, or identify exploitable inefficiencies in the market. However, volatility is not constant over time it exhibits time varying cyclical properties such as clustering, a tendency to mean revert, and asymmetric reactions to market shocks (leverage effect, where negative excess returns lead to greater volatility than positive ones). These time varying properties of volatility necessitate the use of more advanced models that can incorporate both short term and long-term shocks.

Accurate prediction of volatility is crucial as mentioned earlier. While various models exist to capture the time-varying nature of volatility, this application part focuses on leveraging the power of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Autoregressive Moving Average (ARMA) model as an assistant in refining our volatility predictions.

The GARCH model has evolved into a critical tool for forecasting volatility. The (GARCH) model was developed by Bollerslev in 1986 as a generalization of the ARCH process. The extension from the ARCH model to the GARCH model allows for the inclusion of past conditional variances in the current conditional variance equation (Nordstro, 2021). This enhancement enables the GARCH model to capture key stylized facts of financial returns, particularly volatility clustering and persistence. The GARCH model primarily focuses on fluctuations in variance over time but often assumes that the conditional mean of the time series remains constant. In other words, the model analyzes how risk (variance) evolves while assuming that the overall level remains unchanged.

In many real-world financial applications, the conditional mean of returns may exhibit serial correlation. This is where the ARMA model comes into play. ARMA models are well-suited for capturing the autoregressive and moving average components in the conditional mean of a time series. By effectively modeling the predictable patterns in the returns themselves, we can potentially obtain more accurate estimates of the residuals (the unpredictable component), which in turn drive the volatility process modeled by the GARCH framework.

By integrating the strengths of both ARMA and GARCH models, our goal is to develop a more comprehensive and potentially more accurate framework for volatility forecasting. In this practical section, we will walk through the key steps of the process, including model selection, parameter estimation, and the evaluation of forecasting accuracy.

1. Overview of the data:

1.1. Type of Study:

This research is a quantitative analysis that uses econometric modeling and statistical analysis to test hypotheses and predict price volatility of financial assets. It is based on time series analysis in which modelling conditional heteroscedasticity is an important element of capturing the behavior of returns on financial markets. This analysis focuses on modelling and forecasting the volatility of emerging market equities which tend to be more volatile than developed markets and are more sensitive to global economic and financial shocks.

1.2. Data Sources:

The data for this study consists of historical daily closing prices of the iShares MSCI Emerging Markets ETF (EEM). The EEM ETF is selected because it is a widely traded and liquid instrument that provides broad exposure to emerging market equities.Closing prices are chosen specifically because they tend to exhibit greater volatility, which makes them particularly suitable for econometric analysis focused on price dynamics. These data were obtained from Yahoo Finance, a dependable source of historical financial data that is useful for econometric analysis.

1.3. Time Period of Analysis:

The sample period extends from April 23, 2003, to September 24, 2024. April 23, 2003, is selected as the starting point because it marks the date with fully available and reliable trading data following the fund's launch on April 14, 2003. This period encompasses a range of market conditions, including periods of economic growth, financial crises, and periods of relative stability, allowing for a robust analysis of volatility dynamics.

The dataset is split into two sub-periods:

1.3.1 Estimation Period:

April 23, 2003, to March 24, 2024. This period is used to estimate the parameters of the volatility forecasting model.

1.3.2 Forecast Period:

March 25, 2024, to September 24, 2024. This period is used to evaluate the out-of-sample forecasting performance of the model by comparing predicted volatility with realized market behavior during this period.

2. Methodology:

The ARMA-GARCH model is an important framework for analyzing financial time series data that exhibits both autocorrelation in returns and changing volatility over time. The ARMA-GARCH model is a hybrid model that takes advantage of two important econometric models. Together, the ARMA-GARCH framework models both the conditional mean and conditional variance jointly.

2.1. ARMA Model:

An Autoregressive Moving Average model, or ARIMA, is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends. A statistical model is autoregressive if it predicts future values based on past values. For example, an ARIMA model might seek to predict a stock's future prices based on its past performance or forecast a company's earnings based on past periods (Hayes, 2024). It is useful in capturing linear dependencies and autocorrelations within financial returns.

Often this model is referred to as the ARMA(p,q) model, where:

- **p**: is the order of the autoregressive polynomial.
- **q**: is the order of the moving average polynomial.

The equation is given by:

$$y_t = \underbrace{\phi_1 y_{t-1} + \cdots + \phi_p y_{t-p}}_{\text{AR}} + \underbrace{\theta_i w_{t-1} + \cdots + \theta_q w_{t-q}}_{\text{MA}}$$

With $\boldsymbol{\phi_p \neq 0}$, $\boldsymbol{\theta_q \neq 0}$, and $\boldsymbol{\sigma_w^2 > 0}$. The equation can be rewritten as:

$$y_t = \underbrace{\sum_{i=1}^{p} \phi_i y_{t-i} + w_t}_{\text{AR}} + \underbrace{\sum_{i=0}^{q} \theta_i w_{t-i}}_{\text{MA}}$$

2.2. GARCH Model:

The past squared observation value and past variance are used by the GARCH model to model the variance at time t. The conditional variance is allowed to depend on prior lags by the model. The models gauge how much a volatility shock from today will affect volatility in the coming term. It gauges how quickly this effect has subsided over time. The definition of GARCH (p,q) model is (Kennedy, Cynthia, & Oyinebifun, 2023):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2$$

where :

- $\boldsymbol{\alpha_0}$: is the constant coefficient.
- $\boldsymbol{\alpha_i}$: are parameter estimates.
- $\boldsymbol{\beta_i}$:are the conditional variance for y_t.

Analysis Tools: All data processing, estimation, and forecasting procedures are conducted using OxMetrics 7.2, a powerful econometric software suite designed for advanced time series analysis. The software includes PCGive, which offers flexible tools for linear dynamic models, and the G@RCH module, which is tailored for modeling conditional heteroskedasticity.

3. Results and discussion:

3.1. Descriptive statistics and graphical representation of closing prices:

The table presents descriptive statistics for the mean, standard deviation, and median of a series of closing prices, while the chart illustrates the historical development of this daily closing price series from 2003-04-23 to 2024-03-24.

Table 1: Descriptive statistics of closing prices.

Tests	Mean	Median	Max	Min	Std.Dev	Skewness	Kurtosis	Jarque-Bera
Close	38.236	40.100	57.960	11.238	9.153	-0.900	3.492	764.185

Source: Outputs of the Oxmetrics 7.2

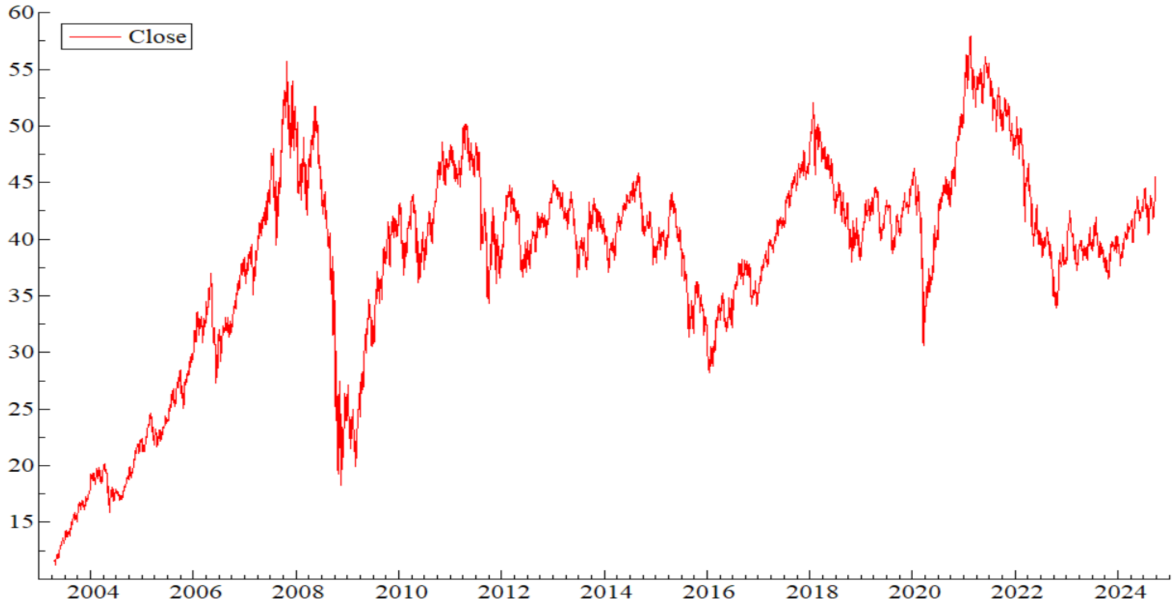
From the descriptive statistics for the "Close" variable the following can be noted:

The mean **(38.23)** and median **(40)** are close, suggesting a central tendency symmetry, but the negative skewness **(-0.90)** indicates a left-skewed distribution. This is further supported by the mean being slightly lower than the median. Despite the proximity of the mean and median, we chose to apply a logarithmic transformation to the price values to further stabilize the distribution. This transformation helps reduce the impact of outliers, which is beneficial for many statistical analyses and modeling techniques.

The maximum close value observed is (**57.96**), while the minimum is (**11.23**), indicating a considerable range of price volatility during the observed period.

As for the Jarque-Bera test, the statistic reached (**764.18)**, this leads to the rejection of the null hypothesis at the 5% significance level. This suggests that the distribution distribution of the closing price data does not follow a normal distribution.

Figure 1: Time Series Plot of the Closing Prices of the iShares MSCI Emerging Markets ETF (EEM).



Source: Outputs of the Oxmetrics 7.2

The graph represents the changes in closing prices over time, revealing that the variance is not constant, which suggests that the series is not stationary. A sharp decline is observed in 2008, corresponding to the global financial crisis and the drop in stock prices. Another decline appears around 2016, coinciding with a fall in oil prices and a slowdown in global economic growth. A further sharp decrease occurred in early 2020, attributed to the COVID-19 pandemic and its widespread economic impact. Following a partial recovery, the year 2022 witnessed fluctuations influenced by the war in Ukraine and mounting global inflationary pressures.

3.2. First Step: Tests on EEM (MSCI) Prices.

We chose to work specifically with closing prices because they capture the most comprehensive and consolidated information about market activity within a trading day, reflecting the daily consensus value of an asset. Additionally, volatility patterns and price shocks, observable in closing prices, make them ideal for identifying and analyzing volatility spikes and trends over time. To estimate representative models for the behavior of the closing price, it is essential to use a stationary series. Therefore, stability tests, such as the ADF and KPSS tests, must be employed to ensure that the series is stationary.

3.2.1. ADF Test (Augmented Dickey-Fuller):

Hypotheses:

- **H_0 (Null Hypothesis):** There exists a unit root in the time series and it is non-stationary.
- **H_1 (Alternative Hypothesis):** There exists no unit root in the time series and it is stationary.

If the test statistic is less than the critical value or if the p-value is less than a pre-specified significance level (e.g., 0.05), then the null hypothesis is rejected, and the time series is considered stationary.

If the test statistic is greater than the critical value, the null hypothesis cannot be rejected, and the time series is considered non-stationary.

Table 2: ADF (Augmented Dickey-Fuller) Test.

ADF test	Degree of lag	Calculated value	Critical value 5%	Critical value 1%
Test without constant and trend	**2**	**-0.0025**	**-1.939**	**-2.566**
Test with constant	**2**	**-3.159**	**-2.863**	**-3.435**
Test with constant and trend	**2**	**-3.134**	**-3.413**	**-3.965**

Source: Outputs of the Oxmetrics 7.2

The results presented in the table indicate that the calculated ADF values, which are (**-0.0025**) and **(-3.134)** respectively, are greater than the critical values at the 5% significance level. Therefore, the null hypothesis (H_0) is not rejected, implying that the series is non-stationary. However, when the test is conducted with a constant, the calculated ADF value is **(-3.159)**, which is less than the critical value at the 5% significance level. Thus, the null hypothesis (H_0) is rejected, indicating that the series is stationary.

Based on the above, it can be concluded that the closing price series is overall non-stationary. To further verify the stationarity or non-stationarity of the series, a KPSS test will be conducted. We rely on both the ADF and KPSS tests because their null hypotheses are opposite: the ADF test assumes non-stationarity (the presence of a unit root), while the KPSS test assumes stationarity. By conducting both tests, we obtain a more comprehensive assessment of the series' stationarity. Additionally, the KPSS test is more sensitive in detecting other types of instability, such as random trends and long memory, which might not be identified by the ADF test alone.

3.2.2. KPSS Test (Kwiatkowski–Phillips–Schmidt–Shin):

Hypotheses:

- **H_0 (Null Hypothesis):** The time series is stationary (either stationary around a mean or stationary around a trend).
- **H_1 (Alternative Hypothesis):** The time series is non-stationary (due to the presence of a unit root or a random trend).

If the KPSS statistic is greater than the critical value, we reject the null hypothesis, indicating non-stationarity.

Table 3: KPSS (Kwiatkowski–Phillips–Schmidt–Shin) Test.

KPSS test	Degree of lag	calculated value	Critical value 5%	Critical value 1%
Test with constant	**2**	**3.514**	**0.463**	**0.739**
Test with constant and trend	**2**	**0.710**	**0.146**	**0.216**

Source: Outputs of the Oxmetrics 7.2

The results shown in the table indicate that the calculated KPSS values, **(3.514)** and **(0.710)** respectively, exceed the critical values at the 5% significance level. Therefore, the null hypothesis (H_0) is rejected, indicating that the series is non-stationary.

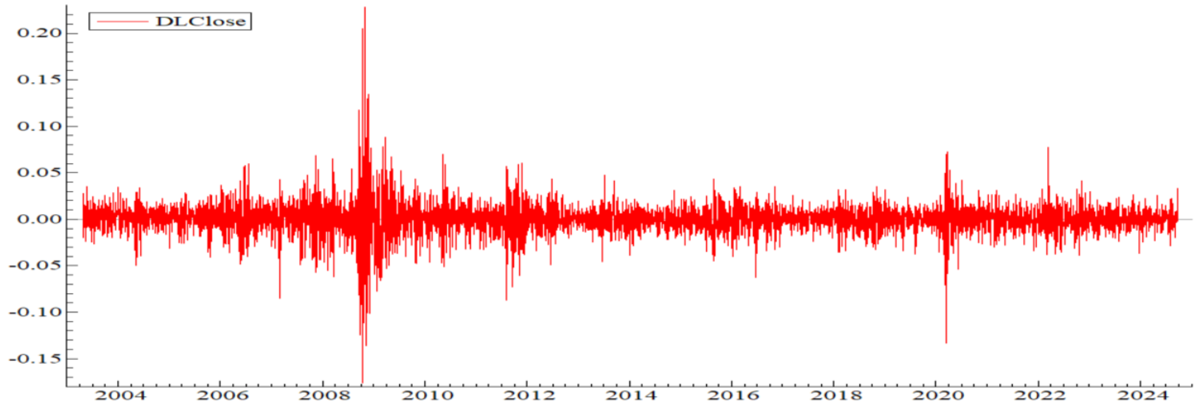
The ADF test results indicate that the series is non-stationary in most cases. Similarly, the KPSS test supports this conclusion. Therefore, it can be concluded that the close series is non-stationary.

3.3. Second Step: Tests on EEM (MSCI) Returns.

As is well known, financial time series are generally non-stationary by nature. To accurately capture the behavior of the closing price series, it is essential for the data to be stationary. Therefore, the first difference will be applied to the series.

After applying the logarithm to the series and transforming it into first differences, commonly referred to as the log returns of the closing price, the resulting series will be denoted as DLClose**.**

Figure 2: Time Series Plot of the First Difference of Closing Prices



Source: Outputs of the Oxmetrics 7.2

The line plot represents the variations in the returns of the closing price over time. This transformation has reduced the trend and provides insight into daily price fluctuations. A visual inspection suggests that the series may be stationary. however, statistical tests are required to confirm this.

3.3.1 ADF Test (Augmented Dickey-Fuller):

Table 4: ADF Test (DLClose).

ADF test	Degree of lag	calculated value	Critical value 5%	Critical value 1%
Test without constant and trend	2	-43.56	-1.939	-2.566
Test with constant	2	-43.58	-2.863	-3.435
Test with constant and trend	2	-43.62	-3.413	-3.965

Source: Outputs of the Oxmetrics 7.2

The results in the table show that the calculated ADF values for the cases of constant with trend, constant without trend, and without constant and without trend are smaller than the critical values at the 5% significance level. Therefore, the null hypothesis (H_0) is rejected, indicating that the series is stationary.

3.3.2 KPSS Test (Kwiatkowski–Phillips–Schmidt–Shin):

Table 5: KPSS Test (DLCose).

KPSS test	Degree of lag	Calculated value	Critical value 5%	Critical value 1%
Test with constant	2	.0272	0.463	0.739
Test with constant and trend	2	0.058	0.146	0.216

Source: Outputs of the Oxmetrics 7.2

The results in the table indicate that the calculated KPSS values for the series with a constant (without trend) and with both a constant and a trend are lower than the critical values at the 5% significance level. Therefore, the null hypothesis (H_0) is not rejected, indicating that the series is stationary.

The results consistently and strongly indicate that the first difference of the logarithm of the closing price (DLClose) for the iShares MSCI Emerging Markets ETF (EEM) is stationary. This means that the series of daily log returns (which DLClose represents) does not have a unit root and its statistical properties (mean, variance) are time-invariant.

3.3.3 Long Memory Tests:

Long memory refers to a situation in which past values of a series exert a persistent influence on future values, often evidenced by slowly decaying autocorrelations. This property, common in financial time series, can complicate model specification and may lead to misleading inferences if ignored.

To capture this characteristic, two specialized tests were conducted: the Hurst-Mandelbrot Rescaled Range (H-M R/S) test and the Lo R/S test. These tests are specifically designed to assess Long Memory, thereby providing deeper insights into the underlying structure of the time series.

Hypotheses:

- **H_0 (Null Hypothesis):** The series is not long-memory.
- **H_1 (Alternative Hypothesis):** The series is long-memory.

Table 6: Long Memory Tests.

Long Memory Tests	Statistical value	Table value at 5%	Table value at 1%
Hurst-Mandelbrot R/S test	1.13252	[0.809, 1.862]	[0.721, 2.098]
Lo R/S test	1.20583	[0.809, 1.862]	[0.721, 2.098]

Source: Outputs of the Oxmetrics 7.2

Hurst-Mandelbrot R/S test: The calculated statistical value of (**1.093)** falls within the 5% critical value range. Since the statistical value lies within the critical value range at the 5% significance level, we fail to reject the null hypothesis of no long-term dependence based on the Hurst-Mandelbrot R/S test. This suggests that there is no statistically significant evidence of long memory in the time series according to this test.

Lo R/S test: The calculated statistical value of (**1.165)** also falls within the 5% critical value range [0.809, 1.862]. Similar to the Hurst-Mandelbrot R/S test, the Lo R/S test fails to reject the null hypothesis of no long-term dependence at the 5% significance level. This provides further evidence that there is no statistically significant long memory in the time series.

3.3.4 ARCH Effects and Autocorrelation Tests:

The ARCH (Autoregressive Conditional Heteroskedasticity) test is a statistical tool used to determine whether the variance of a time series changes over time and depends on the variances of previous periods, a phenomenon known as volatility clustering.

In Figure 2, we observe clusters of volatility in the returns of closing prices (periods where volatility rises and falls together), which indicates the presence of an ARCH effect. To formally confirm this, ARCH tests are conducted to assess whether this conditional heteroskedasticity is statistically significant.

Hypotheses:

- **H_0 (Null Hypothesis):** There is no ARCH effect (i.e., the variance is constant over time - Homoskedasticity).
- **H_1 (Alternative Hypothesis):** There is an ARCH effect (i.e., the variance changes over time – Heteroskedasticity).

Table 7: ARCH-LM Test

ARCH-LM Test	Statistical value	P-value
ARCH 1-2 test	793.94	0.0000
ARCH 1-5 test	440.00	0.0000
ARCH 1-10 test	346.80	0.0000

Source: Outputs of the Oxmetrics 7.2

Based on the table, the p-value is less than 0.05, leading us to reject (H_0). This indicates that the three statistics are statistically significant, providing clear evidence of ARCH effects and suggesting that the variance of returns changes over time.

The Q statistic is applied to raw data to test whether there are statistically significant correlations between the values of the time series across different time periods, revealing linear dependence. In contrast, the Q statistic is applied to squared data to detect autocorrelation in volatility. If large volatilities are followed by large ones and small volatilities are followed by small ones, this indicates the presence of an ARCH effect.

Hypotheses (Raw data):

- **H_0 (Null hypothesis):** No autocorrelation up to lag h (i.e., residuals are white noise).
- **H_1 (Alternative hypothesis):** At least one autocorrelation up to lag h is non-zero.

Hypotheses (Squared data):

- **H_0 (Null hypothesis):** No autocorrelation in the squared series up to lag h (i.e., no ARCH effects).
- **H_1 (Alternative hypothesis):** At least one autocorrelation in the squared series is non-zero (i.e., ARCH effects present)

Table 8: Box-Pierce Q-Statistics on (Raw data - Squared data) Test.

	On Raw data (autocorrelation)		On Squared data (ARCH effects)	
Degree of lag	**Value**	**P-value**	**Value**	**P-value**
Q (5)	**97.1075**	**0.0000000**	**2598.25**	**0.0000000**
Q (10)	**105.952**	**0.0000000**	**5160.33**	**0.0000000**
Q (20)	**200.015**	**0.0000000**	**9412.30**	**0.0000000**
Q (50)	**269.092**	**0.0000000**	**12765.1**	**0.0000000**
Q (75)	**328.515**	**0.0000000**	**13164.4**	**0.0000000**

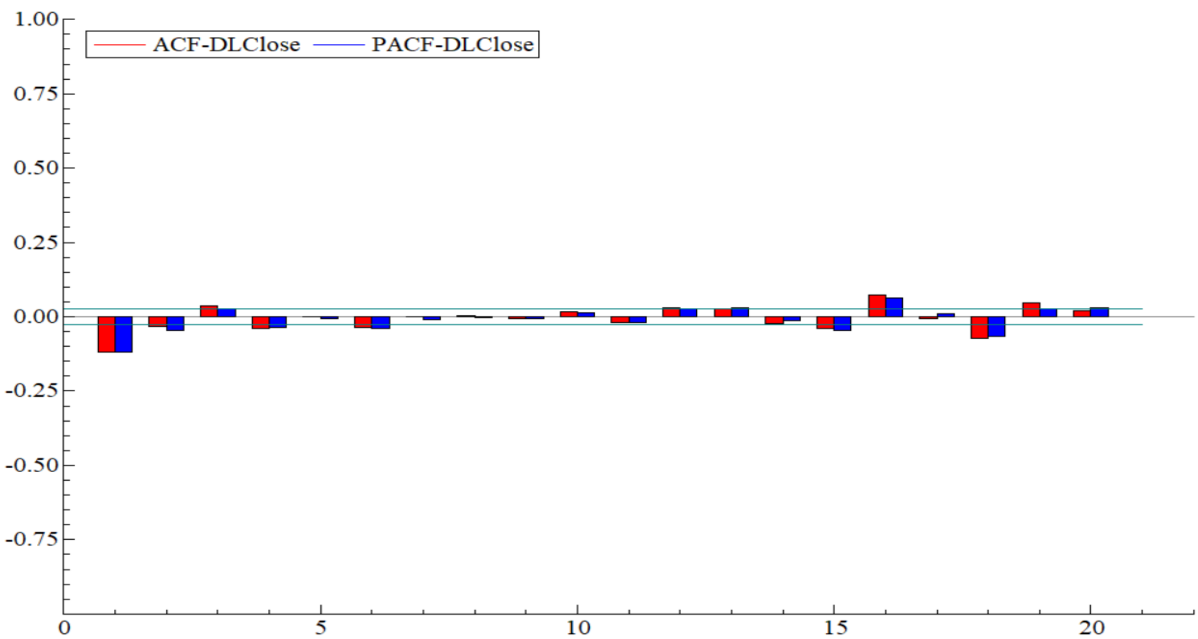
Source: Outputs of the Oxmetrics 7.2

Based on the table, the p-values for both the raw data and the squared data are less than 0.05. Therefore, we reject the null hypothesis (H_0), indicating the presence of serial correlation and ARCH effects.

3.4. Third Step: Building the Mean Model and Generating Residuals

Based on the results of the previous tests, and given that the series becomes stationary after first differencing, we conclude that an ARMA(p, q) model is appropriate for our data in order to generate the residual series required for modeling volatility.

Figure 3: ACF and PACF of Daily Log Returns (DLClose).



Source: Outputs of the Oxmetrics 7.2

Based on the plot, there is a strong negative autocorrelation at lags 1 and 2 in both the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the daily log-return series (DLClose). Beyond these lags, the values of the ACF and PACF decline rapidly and fall within the confidence bounds, indicating no statistically significant autocorrelations at higher lags. This pattern suggests that the time series dependency is primarily concentrated in the immediate past, particularly at lag 1.

Comparison of ARMA models based on the Akaike Information Criterion (AIC) and the value of the log-likelihood function:

Table 9: Comparison of ARMA Models Based on AIC and Log-Likelihood Values.

ARMA Models	AIC value	Value log-likelihood
ARMA (1,0)	**-5.27507212**	**14223.5944**
ARMA (0,1)	**-5.27616868**	**14226.5508**
ARMA (1,1)	**-5.27633729**	**14228.0053**
ARMA (1,2)	**-5.27799179**	**14233.4659**
ARMA (2,1)	**-5.27836872**	**14234.4821**
ARMA (2,2)	**-5.27802302**	**14234.5501**

Source: Outputs of the Oxmetrics 7.2

To select the optimal model, we adopted the approach of minimizing the information criterion, specifically the Akaike Information Criterion (AIC), and maximizing the log-likelihood. The table above presents the estimated values for the candidate models. The model parameters were estimated using the maximum likelihood estimation (MLE) method, ensuring efficient and consistent parameter estimates. The best model was selected by comparing the AIC values and choosing the one with the lowest AIC, which is (**-5.27836872**), corresponding to the **ARMA(2,1)** model.

3.5. Fourth Step: Variance Modeling

3.5.1 Sub-step 1: Tests for Long Memory, Autocorrelation, and ARCH Effects

We will examine the residuals to detect ARCH effects by testing for time-varying volatility. Additionally, the residuals will be tested for the presence or absence of serial correlation between the values. Furthermore, long-memory tests will be conducted to assess whether there is long-term dependence in the data.

Long Memory Tests:

Table 10: Long Memory Tests (ARMA (2,1)).

Long Memory Tests	Statistical value	Table value at 5%	Table value at 1%
Hurst-Mandelbrot R/S test	**1.30477**	**[0.809, 1.862]**	**[0.721, 2.098]**
Lo R/S test	**1.30468**	**[0.809, 1.862]**	**[0.721, 2.098]**

Source: Outputs of the Oxmetrics 7.2

The Hurst-Mandelbrot R/S test was conducted, yielding a test statistic of (**1.30477**), which falls within the 5% critical value range, resulting in the failure to reject the null hypothesis of no long-term dependence. Similarly, the Lo R/S test produced a test statistic of (**1.30468**), which also lies within the critical value range [0.809, 1.862], further supporting the results of the Hurst-Mandelbrot test and suggesting the absence of long memory in the time series.

ARCH Effects and Autocorrelation Tests:

Table 11: ARCH-LM Test (ARMA (2,1)).

ARCH-LM Test	Statistical value	P-value
ARCH 1-2 test	818.44	0.0000
ARCH 1-5 test	457.11	0.0000
ARCH 1-10 test	345.22	0.0000

Source: Outputs of the Oxmetrics 7.2

As shown in the table, all p-values are below the 0.05 threshold, indicating that the corresponding coefficients are statistically significant. This provides evidence of the presence of ARCH effects in the residuals.

Table 12: Box-Pierce Q-Statistics (ARMA (2,1)).

	On Raw data (autocorrelation)		On Squared data (ARCH effects)	
Degree of lag	Value	P-value	Value	P-value
Q (5)	4.26263	0.5122566	2516.17	0.0000000
Q (10)	11.6015	0.3126106	4890.92	0.0000000
Q (20)	85.9238	0.0000000	8974.38	0.0000000
Q (50)	151.619	0.0000000	12272.7	0.0000000
Q (75)	212.305	0.0000000	12670.6	0.0000000

Source: Outputs of the Oxmetrics 7.2

The table presents the results of the Ljung-Box Q test on both raw and squared data at different lag lengths. The majority of low p-values (less than 0.05) in the raw data test indicate the presence of serial correlation in the levels of the series. Similarly, very low p-values in the squared data test suggest a strong ARCH effect, meaning that current volatility depends on past volatilities. These results highlight the necessity of modeling volatility using models such as GARCH

3.5.2 Sub-step 2: Parameter Estimation

Based on the results of the previous tests and in an effort to accurately model the volatility and clustering behavior observed in financial returns, a series of GARCH(p, q) models with varying lag orders were estimated. This process was guided by diagnostic tests, including the Box-Pierce test applied to the standardized residuals and their squared values, as well as the LM test for detecting ARCH effects.

To further ensure the robustness of the volatility modeling, several ARCH and GARCH specifications were initially estimated. However, diagnostic tests on the resulting residuals revealed persistent autocorrelation, indicating that the models did not fully capture the underlying dynamics. As a result, an ARMA-GARCH model was applied to the residual series to simultaneously account for both the conditional mean and conditional variance. This combined approach enhances the model's goodness of fit and ensures a more accurate theoretical foundation for the forecasting stage, which will be addressed in the third part of this research.

After evaluating the performance of these models, the **ARMA(2,1)–GARCH(1,2)** specification was selected as the most appropriate and efficient. It passed all diagnostic checks (mentioned bellow), and its estimated parameters were statistically significant, indicating a strong fit to the data. Therefore, this model is deemed reliable for capturing and forecasting market volatility with precision.The following section presents the diagnostic test results for the selected model.

This model was estimated under four different distributions for the standardized residuals: Student's t, Generalized Error Distribution (GED), Skewed Student's t (Generalized Skewed Student), and the Gaussian (Normal) distribution. The estimation was conducted using the BFGS method. Among these, the best fit was achieved under the Skewed Student, as indicated in the table:

Table 13: Estimated Coefficients and Statistical Significance of the ARMA (2,1)–GARCH (1,2) Model Parameters.

Degree of lag	Coefficient	Std.Error	P-value
Cst(M)	0.000543	0.00018021	0.0026
AR(1)	-0.576677	0.095455	0.0000
AR(2)	0.078249	0.015920	0.0000
MA(1)	0.648210	0.094933	0.0000
Cst(V) x 10^4	0.051130	0.011959	0.0000
ARCH(Alpha1)	0.042271	0.016351	0.0098
ARCH(Alpha2)	0.065322	0.022811	0.0043
GARCH(Beta1)	0.870245	0.017255	0.0000
Asymmetry	-0.125949	0.020218	0.0000
Tail	9.767995	1.2392	0.0000

Source: Outputs of the Oxmetrics 7.2

The estimated ARMA(2,1)-GARCH(1,2) model with a Student's t-distribution for the error term can be mathematically represented as follows:

Mean Equation ARMA (2,1):

$$r_t = c + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \theta_1 \epsilon_{t-1} + \epsilon_t$$

$$\varepsilon_t = z_t \sqrt{h_t}$$

Where:

- $\boldsymbol{r_t}$: is the return at time t.
- $\boldsymbol{c}$: is the constant term.
- $\boldsymbol{\phi_1}$: is the autoregressive coefficient of order 1.
- $\boldsymbol{\phi_2}$: is the autoregressive coefficient of order 2.
- $\boldsymbol{\theta_1}$: is the moving average coefficient of order 1.
- $\boldsymbol{\epsilon_t}$: is the error term at time t.
- $z_t \sim t_\nu(0,1)$, i.e., a standardized skewed Student's t − distribution with degrees of freedom $\nu = 9.765841$.

Accordingly, the equation takes the following form:

$$r_t = 0.000543 - 0.576677 r_{t-1} + 0.078249 r_{t-2} + 0.648210 \epsilon_{t-1} + \epsilon_t$$

$$\epsilon_t \sim \frac{1}{\sigma_t} t(9.767995)$$

Variance Equation GARCH (1,2):

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \beta_1 \sigma_{t-1}^2$$

Where:

- $\boldsymbol{\sigma_t^2}$: is the conditional variance at time t.
- $\boldsymbol{\omega}$: is the constant term for the variance (represented as Cst(V) in the table).
- $\boldsymbol{\alpha_1}$: is the coefficient for the first lag of the squared error term ARCH(Alpha1).
- $\boldsymbol{\alpha_2}$: is the coefficient for the second lag of the squared error term ARCH(Alpha2).
- $\boldsymbol{\beta_1}$: is the coefficient for the first lag of the conditional variance GARCH(Beta1).

Accordingly, the equation takes the following form:

$$\sigma_t^2 = (0.051130 \times 10^{-4}) + 0.042271 \epsilon_{t-1}^2 + 0.065322 \epsilon_{t-2}^2 + 0.870245 \sigma_{t-1}^2$$

3.6. Fifth Step: Validation of the Estimated Model

In this final step, we assess the adequacy of the **ARMA(2,1)-GARCH(1,2)** model using diagnostic tests. Specifically, we apply ARCH effect tests and Box–Pierce Q-statistics to the residuals and squared residuals. These tests help determine whether the model successfully captures the volatility and autocorrelation structure of the data. A good model should leave no significant patterns in the residuals.

ARCH Effects and Autocorrelation Tests:

Table 14: ARCH-LM Test (ARMA (2,1)–GARCH (1,2))

ARCH-LM Test	Statistical value	Value
ARCH 1-2 test	1.6675	0.1888
ARCH 1-5 test	0.72273	0.6063
ARCH 1-10 test	0.79619	0.6326

Source: Outputs of the Oxmetrics 7.2

Based on the table, since all p-values are greater than the 5% significance level, we fail to reject the null hypothesis of no ARCH effects. This suggests that the volatility model used has effectively captured the volatility dynamics.

Table 15: Box-Pierce Q-Statistics (ARMA (2,1)-GARCH (1,2))

	On Raw data(autocorrelation)		On Squared data (ARCH effects)	
Degree of lag	**Value**	**P-value**	**Value**	**P-value**
Q (5)	**9.28788**	**0.0096197**	**3.59585**	**0.1656422**
Q (10)	**11.1370**	**0.1327534**	**7.79612**	**0.1656422**
Q (20)	**20.2537**	**0.2614588**	***16.8493***	**0.4646180**
Q (50)	**54.9232**	**0.1995415**	**53.3071**	**0.2445912**
Q (75)	**76.2275**	**0.3442274**	**89.2247**	**0.0823842**

Source: Outputs of the Oxmetrics 7.2

The table presents the results of the Ljung–Box statistical test applied to both the raw data residuals and their squared data counterparts at various lags (5, 10, 20, 50, 75), with the aim of assessing the adequacy of the model in capturing both the mean behavior and volatility dynamics. All p-values were found to be greater than 0.05 for both the raw data residuals and the squared data, indicating the absence of autocorrelation in the former and no remaining ARCH effects in the latter. Therefore, it can be concluded that the **ARMA(2,1)-GARCH(1,2)** model successfully captures the key statistical properties of the series.

Table 16: The Adjusted Pearson Chi-square Goodness-of-Fit Test

Cells(g)	**Statistical value**	**P-Value(g-1)**	**P-Value(g-k-1)**
40	**34.4720**	**0.676406**	**0.222403**
50	**41.0684**	**0.782508**	**0.380019**
60	**50.2934**	**0.783041**	**0.421997**

Source: Outputs of the Oxmetrics 7.2

The table presents the results of the Adjusted Pearson Chi-square Goodness-of-Fit Test using different numbers of cells (g = 40, 50, 60) to assess the fit of the data to the Skewed Student distribution, taking into account the number of estimated parameters (k = 10). For each case, the table reports the chi-square statistic and two p-values: the first based on the degrees of freedom (g−1), and the second based on the adjusted degrees of freedom (g−k−1).

The null hypothesis states that the data follow the Skewed Student distribution, while the alternative hypothesis posits a lack of fit.

Since all p-values are greater than 0.05, we fail to reject the null hypothesis in all cases. This suggests that the data do not show a statistically significant deviation from the Skewed Student distribution, indicating that this distribution adequately represents the data.

Chapter conclusion:

In conclusion, the analysis of the iShares MSCI Emerging Markets ETF closing prices demonstrated non-stationarity in the raw data, which was resolved through log transformation and first differencing. While long memory was not detected in the stationary log returns, ARCH effects were evident, necessitating the use of a GARCH model to capture the time-varying volatility. After evaluating several models, the ARMA(2,1)-GARCH(1,2) model with a Skewed Student distributed error term proved to be the most suitable, successfully passing diagnostic tests for residual autocorrelation and remaining ARCH effects. This model provides a solid foundation for the forecasting analysis to be undertaken in the third chapter

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Chapter Two : Risk Management

Chapter Introduction

In recent years, a considerable amount of scholarly and practitioner attention has focused on emerging financial markets as a result of the rapid growth of these markets and their increasing interconnectedness with the global economy. Emerging financial markets, as the name suggests, are subject to a higher volatility regime, have weak or ineffective regulatory structures, and deal with different categories of risk than developed markets, can create both risks and opportunities for investors and financial institutions. Overall, while there is an increasing interest in risk management in emerging markets, the knowledge base remains incomplete, and there is no comprehensive risk management framework that specifically designed for emerging financial markets. While researchers have introduced the study of individual risk factors in emerging markets, like currency risk, political risk, or liquidity risk, there is very limited scholarship on integrated risk exposure and risk management considerations of emerging markets.

Risk is an intrinsic and unavoidable part of nearly every human activity, whether it is a decision made by an individual or the actions of a global investment firm. A number of strategic standards and frameworks have been developed to address these situations, involving collaborative regulatory oversight, aligned governance approaches and policies, as well as a variety of specific financial or investment tools like diversification, hedging, insurance, and quantitative models.Financial theories such as value at risk (VaR), modern portfolio theory, and the capital asset pricing model provide stakeholders with frameworks to assess and take action related to risk.

The critical need for effective risk measurement particularly in the rapidly moving world of markets makes this an important desire. This chapter will focus on the methods available for evaluating and measuring risk. The inherent complexities of financial time series in these markets, such as non-constant volatility and other specific distributional features, often pose challenges to simpler risk assessment frameworks. It is recognized that the validity of any risk measure, like Value-at-Risk, heavily depends on the underlying model and its assumptions. The objective of this chapter is to identify and assess techniques capable of capturing the nuanced characteristics of the financial data under review, thereby progressing towards a more robust framework for risk quantification

1. Definition and history of risk management:

The management of risk in emerging financial markets consists of the identification, measuring, and mitigating of uncertainty that can potentially threaten financial security. Originally, risk management was a straightforward set of risk avoidance measures, has gradually grown into a sophisticated field of study that uses financial models to try to predict market volatility. Risk is an inherent and critical factor that requires management. Accordingly, risk management in emerging markets is the systematic process of identifying, measuring and mitigating exposures to enhance security and stability.

1.1. History of risk management:

The study of risk management in its contemporary concept began after World War II, initially focusing on the use of market insurance to protect against various losses (Dionne, 2013). However, the concept has existed since ancient times. Therefore, we will review the key stages that risk management has gone through (Waal & Versluis, 2017):

Early Practices: The first examples of risk managing date back to the 17th or 18th century, which included some agreements among rice farmers in Japan and their buyers to deliver rice at preset prices. This was similar to the futures contracts used today. This helped reduce their exposure to risks associated with agricultural production and price fluctuations.

Financial Sector Growth: Over the centuries, risk management has becoming increasingly critical for the financial/insurance sector. In the 1980s, significant U.S. banks began developing formal specialized departments to consider and evaluate financial risk management, signalling the importance of the field.

Crises and Adoption of ERM: The 1990s witnessed multiple crises (e.g., the collapse of Barings Bank), underscoring the need for a holistic, enterprise-wide approach to risk management, which in turn led to the acceptance of Enterprise Risk Management (ERM). ERM extended beyond financial department risks to encompass a wide range of risks across the entire organization.

Regulatory Developments: Major regulatory requirements arose (for example, the Sarbanes Oxley Act of 2002) which made publicly traded companies in the U.S. disclose their internal controls and risk management practices. In 2004, Basel II also made banks hold minimum capital for risk, which showed the importance of good risk management.

1.2. definition of risk:

Risk has been defined in various ways by different source:

The Oxford English Dictionary definition of risk is as follows: "a chance or possibility of danger, loss, injury or other adverse consequences". (Hopkin, 2017)

Similarly, The Institute of Risk Management (IRM) defines risk as the combination of the probability of an event and its consequence. (Hopkin, 2017)

The risk was also defined as: A risk is an uncertain event with consequences for an objective. (Waal & Versluis, 2017)

In addition, (Hubbard, 2009) presented two definitions of risk: “Long definition: The probability and magnitude of a loss, disaster, or other undesirable event. Shorter (equivalent) definition: Something bad could happen”.

1.3. definition of risk management:

In a corporate context, risk management means proactively detecting, analysing, and mitigating current and potential risks that could negatively impact the financial health and objectives of the company. (Sutton, 2024)

From a trading perspective, Risk management is about identifying, evaluating, and monitoring the risks according to the conditions and strategy, it is personal. This process helps us find the best risk-reward ratios and have good and profitable trades. (Samimi, Bozorgian, & Samimi, 2022)

More broadly, Risk management is the process by which we try to manage the uncertainty surrounding the objectives. The purpose of the risk management process is to ensure that these objectives are attained. (Waal & Versluis, 2017)

From the prior definitions, we define Risk management is the systematic process of identifying, analyzing, and addressing risks in order to achieve objectives. Within a corporate environment, it is about ensuring that the company's financial standing and goals are protected against potential threats. In trading, it is a tool of risk reward analysis in order to generate profitable trades. Generally, it deals with managing uncertainties to ensure the successful attainment of objectives.

2. Significance of Risk Management in Emerging Markets:

Risk management is a crucial factor in emerging markets because of the challenges and advantages that are specific to these markets. Emerging markets, defined by relatively high economic growth and industrialization, are rich with potential for investment and development. However, they are also characterized by higher risks, such as political risks, economic risks, regulatory risks, and risks associated with less developed financial markets:

High levels of uncertainty and volatility are one main reason risk management is important in emerging markets. Often, changes in economic conditions happen quickly in emerging markets, due to changing commodity prices, currency fluctuations, and the changing trade environment. By using strong risk management processes, businesses and investors can protect against currency risks and other negative movements in their investments (Bekaerta & Harveyb, 2002).

Political risk is also a significant aspect that highlights the importance of risk management in emerging markets. Political instability, changes in government policies, and regulatory uncertainty are serious threats to business operations and investments. For example, rapid changes in trade policies can hinder business plans and cause financial damage. Political risk insurance or political risks scenarios are risk management practices used to mitigate risks and provide a cushion against unexpected political events (Bekaerta & Harveyb, 2002).

Additionally, emerging markets tend to have less mature financial and legal systems, which can elevate the risk of fraud, corruption, and issues with contract enforcement. The best way to manage the risk of these issues is to develop solid governance frameworks and put compliance programs in place. Doing so can substantially reduce the probability of having to deal with legal disputes and reputation damage (Porta, Lopez-de-Silan, Shleife, & vishny, 1998).

The management of risk can also improve capital access in developing markets. Businesses that show commitment to risk management are more likely to get funding, and funding on better terms. In emerging markets, expressing confidence in financing alongside improved funding terms is crucial to business expansion (Miller, 1992)

3. Strategic Guidelines for Effective Risk Management in Emerging Markets:

To operate and identify opportunities in emerging markets effectively, you must have a comprehensive plan to mitigate risk. Emerging markets generate many opportunities, however the risks are high, with varying degrees of political instability, market volatility and regulatory hurdles.Utilizing risk assessments and best practices for governance and compliance can ultimately enhance decision-making resilience and help both realize current growth opportunities and navigate risky environments (IOSCO R. o., 1997) **:**

Regulators should work together with market participants to establish and enforce risk management rules. Banks and securities firms should be encouraged to discuss common policies for risk management, and joint regulators in their efforts to minimise systemic risk.

Cooperation agreements between regulators (e.g., banking and broker-dealers regulators) are highly recommended.

Besides capital requirements and other quantitative requisites, regulators should set forth and enforce qualitative requirements for internal controls; financial institutions (and broker-dealers) should be required to have written risk control policies.

There should be an efficient auditing of banks and securities firms with respect to their exposure to risk and their internal controls.

Regulators should develop proper means to supervise firms' activities across different markets (e.g. stock exchanges, futures exchanges, OTC), where applicable, including overseas activities.

Well developed clearing facilities should be in place, in order to enhance risk management at an aggregate level; cooperation agreements between clearings acting in different markets are essential for supervision across markets.

At firm levels, VaR and similar quantitative models are an important tool, but useless without a corporate culture of risk management, that includes proper internal controls, flow of information, engagement of senior management and qualitative standards in general.

Due to the lack of trained professionals, a technical expertise in handling quantitative models should be gradually developed.

Timely identification and management of risks is one of the greatest challenges organizations face, resulting in poorly informed decisions and unexpected loss. This diagram represents the factors and behaviors leading to poor risk management so that deficiencies may be better understood and solutions proposed for improving risk management (Costa, Khan, Levy, Natale, & Tanrikulu, 2014):

Figure 1: The factors and behaviors leading to poor risk management.

Source: (Costa, Khan, Levy, Natale, & Tanrikulu, 2014).

(Scott, Amajuoyi, & Adeusi, 2024) presented risk management's four primary strategies. These strategies are important because they mitigate future obstructions and provide resiliency in unstable environments. They are as follows:

Diversification: Diversification is a strategy to mitigate risk by distributing investments across a range of financial instruments, sectors, and other categories. It seeks to enhance return by investing in a diversity of areas that respond differently to the same event.

Hedging: Hedging entails taking an investment posture that is intended to offset the risk of loss or liability the companion investment may incur. Hedging usually involves the use of derivatives, such as options and futures contracts, to cushion the risk of price fluctuations in the financial marketplace.

Insurance: Insurance in the financial markets is a financial risk management tool that transfers the risk of loss from one party to another for an established premium. Insurance protects the entity against the risk of contingent or uncertain loss.

Risk Assessment Models: Risk assessment models are quantitative financial instruments used to assess the level of risk associated with various types of financial instruments or investment portfolios. The objective of a risk assessment model is to make informed decisions based on measuring the likelihood of loss and the likelihood of other outcomes occurring.

4. Financial Theories for Risk Management:

Over the past few years, numerous theoretical modeling strategies and quantitative tools have been developed to better understand, measure, and manage the risks and returns associated with investments in financial markets. Theoretical models and measurement systems facilitate decision-making for investors, portfolio managers, and policymakers facing the uncertainty that accompanies financial markets. Specifically, the ease of measuring value at risk (VaR) to quantify potential losses, or other assumptions, has collectively contributed to shaping the fundamental principles that underlie contemporary investment analysis and financial practice.

4.1. Value at Risk (VaR):

VaR is a widely used measure that estimates the potential loss in portfolio value over a specified time frame at a given confidence level. For example, a 5% VaR of $1 million indicates a 95% probability that losses will not exceed $1 million during the specified period. However, VaR is limited in its ability to capture extreme tail events, which is where CVaR, or Expected Shortfall, becomes valuable. CVaR estimates the average loss beyond the VaR threshold, providing a more comprehensive view of extreme risks (Oko-Odion & Angela, 2025).

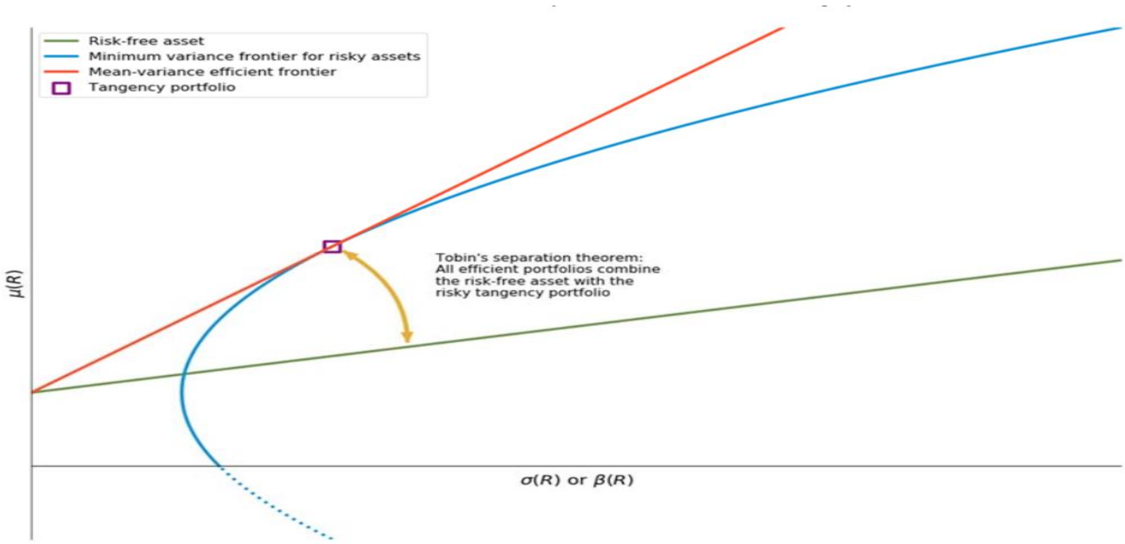
4.2. Modern Portfolio Theory (MPT):

Developed by Harry Markowitz in the 1950s, MPT is a framework for assembling a portfolio of assets such that the expected return is maximized for a given level of risk. It emphasizes the benefits of diversification and is foundational to the concept of the efficient frontier, which shows the most efficient portfolios that provide the best expected return for a given level of risk (Scott, Amajuoyi, & Adeusi, 2024). For example, stock investors can reduce risk by putting a portion of their portfolios in government bond ETFs. The variance of the portfolio will be significantly lower because government bonds have a negative correlation with stocks. Adding a small investment in Treasuries to a stock portfolio will not have a large impact on expected returns because of this loss-reducing effect (The Investopedia Team, 2023).

4.3. Capital Asset Pricing Model (CAPM):

The initial model of market rationality is the capital asset pricing model (CAPM). The CAPM, developed by Sharpe (1964) and Lintner (1965), marks the birth of asset pricing. Building on this foundational framework, the CAPM has become a practical and widely-used tool for estimating the cost of capital for firms and the returns that investors require in investing in a company's assets. The CAPM explains the tradeoff between assets' returns and their risks, measuring the risk of an asset as the covariance of its returns with returns on the overall market. The principal prediction of the model is that the expected return on any two assets is linearly related to the covariance of the return on these assets with the return on the market portfolio. Each asset has two types of risk: diversifiable, or unique, risk and non-diversifiable, or market, risk (Rossi, 2016).

Figure 2: Deriving the CAPM from the mean-variance optimization of a risky portfolio.



Source: (Chen J. M., 2021)

4.4. Arbitrage Pricing Theory (APT):

The APT suggests that the returns on assets follow a linear pattern. An investor can leverage deviations in returns from the linear pattern using the arbitrage strategy. Arbitrage is the practice of the simultaneous purchase and sale of an asset on different exchanges, taking advantage of slight pricing discrepancies to lock in a risk-free profit for the trade. For example, if the fair market value of stock A is determined, using the APT pricing model, to be $13, but the market price briefly drops to $11, then a trader would buy the stock, based on the belief that further market price action will quickly "correct" the market price back to the $13 a share level (Alam, 2022).

The APT can be expressed in an equation based on three basic assumptions (Alam, 2022):

- Capital markets are perfectly competitive.
- Investors always prefer more wealth to less with certainty.
- The stochastic process generating asset returns can be expressed as a linear function of a set of K risk factors (or indexes), and all unsystematic risk is diversified away.

4.5. Efficient Market Hypothesis (EMH):

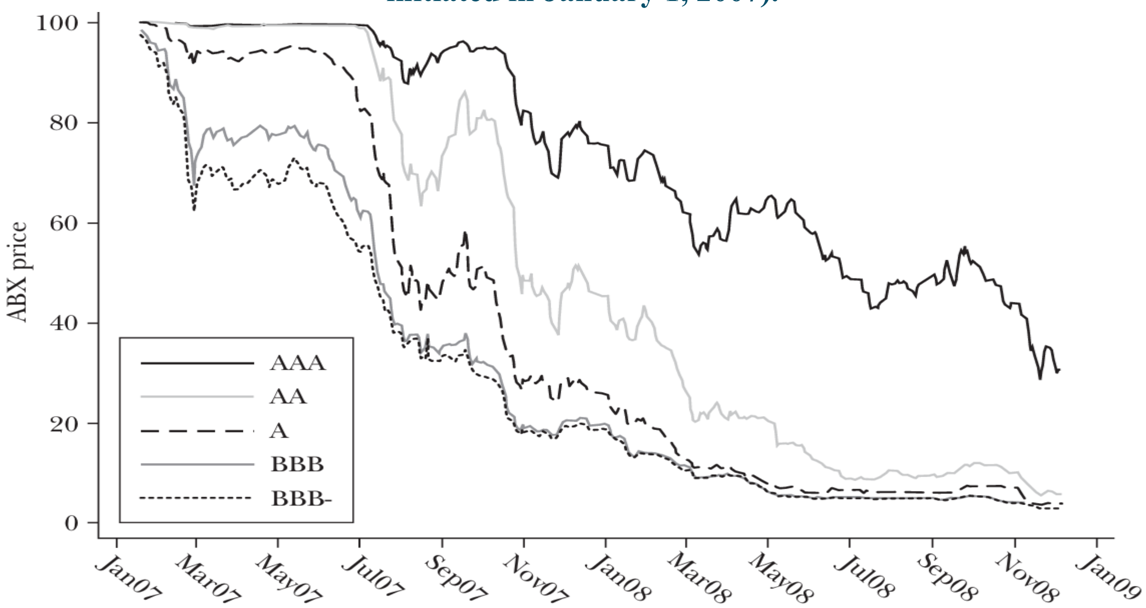
The Efficient Markets Hypothesis (EMH) posits that in a competitive market with rational, profit-maximizing agents, asset prices incorporate all available information, leaving no predictable, riskless profit opportunities unexploited (Gans, 2025). Building on this, the EMH presents participants in financial markets as rational optimizers and therefore assumes that everyone can solve complex stochastic optimization models. The EMH postulates that the arrival of new information into capital markets is presumed to be random, and therefore, the effect on prices cannot be predicted with ease. The EMH also suggests that the actions of irrational optimists or pessimists are offset by "smart money" investors who buy or sell appropriately to eliminate irrational traders. Deviations from the fundamental prices of stocks are therefore short-lived, as the markets are quickly corrected by the actions of intelligent investors. Thus, in an efficient market, it is impossible to predict the direction of the market using technical analysis or by trying to anticipate the emotions of retail investors. The EMH is the basis on which the idea of "passive investing" rests, where investors tend to invest through index funds with the belief that, because it is impossible to consistently beat the market, there is no need to spend more on active portfolio management. According to this line of thought, it is prudent and more rewarding to invest in the entire market at considerably lower costs compared to the costs likely to be incurred by active investors (Nyakurukwa & Seetharam, 2023).

5. Exploring the impact of global crises on risk management strategies:

As the world becomes more interconnected, global crises are occurring more frequently and with greater intensity, rendering traditional risk management strategies increasingly obsolete. Crises have emerged in many areas, including financial crises. These events have forced organizations to reconsider their risk management strategies. This element discusses how global crises have impacted risk management strategies and highlights the need for flexibility, resilience, and proactive planning:

In the past, risk management has focused on financial risks, usually based upon minimizing market fluctuations and credit risk. However, global crises have changed the landscape of risk management to account for a larger element of risk related to operational, reputational, and strategic risks. The financial market turmoil in 2007 and 2008 led to the most severe financial crisis since the Great Depression. This forced banks to write down several hundred billion dollars in bad loans caused by mortgage delinquencies. At the same time, the stock market capitalization of the major banks declined by more than double (Brunnermeier, 2009). Figure 3 shows the ABX price index, which is based on the price of credit default swaps.

Figure 3: Decline in Mortgage Credit Default Swap ABX Indices (the ABX 7-1 series initiated in January 1, 2007).



Source: (Brunnermeier, 2009)

Risk management strategies have undergone significant transformation because of technological advancements. Organizations now better predict and respond to crises because big data analytics is combined with artificial intelligence and machine learning. The COVID-19 pandemic led companies to use data analytics to track supply chain disruptions, which enabled them to modify their operations (Ivanov & Dolgui, 2020). Organizations now use data-driven decision-making to improve their real-time risk anticipation and mitigation capabilities.

Taking proactive risks is a necessity, Proactive risk management seeks to identify risks before they lead to a crisis and develop a risk mitigation plan to lessen the effects of the crisis. Following the Fukushima nuclear disaster in 2011, industry awareness led to enhanced risk management for the nuclear sector and the development of stronger safety regulations and emergency response measures (Kushida, 2012). By being proactive, organizations can reduce the negative impact of crises, including financial ones.

Political tensions are a major risk factor. The Turkish Lira crashed on August 10, 2018 due to a trade spat between USA and Turkey and various economic, political, and financial factors. In this crisis, Turkish Lira (TRY) lost 35% of its value against the US Dollar in 2018 in just 47 days spanning July 1, 2018 to August 16, 2018 with a 17% decline in the stock market and an increase in the government borrowing costs to 18% (Hadi, Karim, Naeem , & Lucey, 2023).

Literature Review:

Emerging financial markets pose a distinctly complex environment for appropriate risk management because of their volatility, regulatory underdevelopment, and external shocks. Emerging markets are defined by rapid growth coupled with high returns, but they are also often subject to political instability, currency fluctuations, and limited good financial data sources. Therefore, traditional risk models developed in established markets may not adequately address the specific dynamics of emerging markets. Over the last decade, literature has also increasingly examined risk management in these markets by arguing that risk management strategies must be contextualized to these environments in light of global financial integration and local vulnerabilities. The literature has included themes such as examining institutional quality, considering the effects of capital flow volatility, and evaluating the applicability of international regulatory standards in emerging settings. As emerging markets develop and continue to play an increasingly important role in the global financial system, the future challenge will be managing risk in emerging markets for policymakers, investors, and academics alike.

Risk management is the cornerstone of financial stability. It involves identifying, evaluating, and controlling potential threats to an organization's capital and earnings. These risks can arise from various sources, including market variability, credit risk, operational risk, and uncertainty. Over the years, the discussion in both academic and practitioner literature has evolved to include numerous complex models and approaches to measuring and managing risk. A review of the literature suggests using a combination of qualitative and quantitative techniques, ranging from conventional methods like value-at-risk (VaR) and stress testing, to contemporary approaches that utilize machine learning and real-time data. More importantly, the financial crises of the past few decades have underscored the need for forward-looking and adaptive risk management frameworks in order to stay abreast of ever-changing economic circumstances.

This review of relevant literature will analyze the academic studies to explore the theoretical underpinnings and methodologies associated with managing risk in emerging financial markets. Its purpose is ultimately to identify areas needing more development so that we can build better tools to produce trustworthy forecasts. Reliable forecasts are necessary for any decision-making, especially for investors and policy-makers interested in the challenges posed by these rapidly degrading and fluctuating markets.

The study by (Das, Kalimipalli, & Nayak, 2022) analyze the influence of globalization on systemic risk in emerging markets with a study of financial institutions situated in multiple regions. Using an empirical analysis of 1,048 financial institutions from 23 emerging markets, organized into five regions, with 369 U.S. institutions as a comparison group, they analyze the systemic risk structure. They utilize an additively decomposable systemic risk score (derived from an interconnection and default risk) and apply a battery of statistical approaches (Granger causality regressions, vector autoregression (VAR), and time series analysis) to quantify systemic risks and forecast defaults. Most importantly, the study identifies considerable regional heterogeneity in systemic risk in emerging markets, and that connectivity underpins this notion. While globalization appears as a latent contributor to overall financial stability, it does not trigger considerable systemic risk spillovers across regions. This study importantly notes systemic risk as a policy tool to manage credit cycles, and contributes to overall financial stability. One of the main contributions of this study is its rigorous modeling framework and its empirical extension of systemic risk assessment in emerging markets, which contributes to finance policy and regulation implications.

Building on this exploration of systemic risk in emerging markets, (Atilgan & Demirtas, 2013) investigate the relationship between downside risk and expected returns in world equity markets, focusing on whether emerging and developed markets differ in their association. The authors assess downside risk by employing both nonparametric and parametric Value at Risk (VaR) approaches, and they apply fixed-effects panel data regressions to examine the relationship between downside risk and expected market returns. The authors include aggregate dividend yield, price-to-earnings ratio, and price-to-cash flow ratio as control variables.

The results indicate that the relationship between downside risk and expected returns is strong and statistically significant in emerging markets. This suggests that investors in emerging markets demand additional compensation for bearing downside risk. The same relationship is substantially weaker in developed markets and disappears once control variables are accounted for.

By emphasizing the distinction in risk and return between emerging and developed markets, the current paper contributes to the literature focusing on downside risk in emerging economies. The empirical approach also highlights the limitations of conventional risk–return models.

In a related effort to understand downside risk, (Strub & Baker, 2011) examine the development and examination of tools for managing downside risk in emerging market equities. The authors particularly examine the relative efficacy of Expected Shortfall (ES) as an alternative to the more frequently employed, Value at Risk (VaR). They utilize historical daily return data, and apply statistical techniques such as Extreme Value Theory (EVT) and the Generalized Pareto Distribution (GPD) to generate estimates of ES and analyze the application of ES as an indicator of tail risk. In addition, the authors consider asset allocation strategies between equities and lower-risk asset classes such as cash and bonds, accounting for downside risk. The analysis utilizes several performance measures such as volatility, expected shortfall, and Sharpe ratios. The findings indicate that ES is a more useful risk measure than VaR because it does not only measure the likelihood of potentially extreme adverse moves but also the magnitude of losses once the threshold is exceeded. This article contributes to the growing body of literature and practice focused on risk management in emerging markets by advocating for the use of Expected Shortfall as a more appropriate risk metric. The article also provides practical guidance for investment professionals seeking to improve risk-adjusted returns through informed capital allocation and downside protection.

Extending the focus to risk management in less liquid markets, (Janabi, 2021) fills an important void in the literature on equity trading risk management by exploring the specific issues of emerging and illiquid markets, using the Moroccan stock market for illustration. The study utilizes Value-at-Risk (VaR) modeling techniques along with matrix algebra methods to develop a risk assessment tool that is practical for emerging financial markets. Real-world application and stress-testing approaches are provided to demonstrate the application of these methodologies in the context of the Casablanca Stock Exchange (CSE).

The results indicate that the methodologies can be utilized in various practical settings within emerging markets, particularly in managing portfolios that contain illiquid securities, while also offering solutions to accommodate the illiquid nature of these markets.

The paper's main contribution lies in its combination of analytical rigor and practical usability. By creating a customizable risk assessment toolbox, supported by empirical examples, the research delivers theoretical insights to investors and risk managers operating in increasingly constrained or less liquid markets characterized by high volatility.

To further investigate how financial development shapes investment behavior, In their research, (Love & Zicchino, 2006) examine the interplay between firms' financial conditions and investment behavior as well as the role of a country's financial development in determining the intensity of financing constraints. The study implements a panel vector autoregression (VAR) model based on firm-level data collected from 36 countries, which allows for the investigation of both financial and fundamental investment determinants without the assumption of restrictive structural forms. They find that firms' investment is particularly sensitive to endogenous shocks, such as internal cash flow, in countries with less financial development. Firms in these less financially developed countries exhibit greater sensitivity of investment to cash flow shocks, whereas firms in more financially developed countries exhibit less import of cash flow to investment decisions and have relatively less sensitivity to shocks to fundamental variables, like marginal productivity. Overall, this paper provides an important contribution to the investment and financial constraints literature by providing empirical evidence of the role of financial development in capital allocation.

From a methodological perspective, (Korobilis & Yilmaz, 2018) make a significant methodological contribution to the measurement of systemic risk by developing a connectedness index based on a large Bayesian time-varying parameter vector autoregressive (TVP-VAR) model. Their study analyzes daily stock return volatilities for 35 major U.S. and European financial institutions over the period from January 2005 to July 2016. The authors develop a dynamic measure of interconnectedness in financial markets by expanding the Bayesian estimation algorithm to allow for uncertainty in the BVAR's covariance matrix and utilizing the framework of the Diebold-Yilmaz Connectedness Index (DYCI).

The findings indicate that the TVP-VAR-based connectedness index is particularly effective in capturing abrupt turning points and crisis episodes, demonstrating stronger responsiveness during times of financial turmoil compared to traditional rolling-window methods. Moreover, the proposed approach exhibits superior forecasting performance in anticipating systemic events. A key strength of this study lies in its novel estimation strategy, which addresses the excessive persistence typically observed in rolling-window estimations and enhances the ability to identify and monitor systemic risks within the financial sector.

Turning to contemporary practices in risk management, (Rahman & Sari, 2023) analyze the changing landscape of risk management practices in financial markets, with an emphasis on current trends and newly developed practices. The study centers on the increasing usage of quantitative risk measurement models, particularly Value at Risk (VaR) and Conditional Value at Risk (CVaR) in conjunction with increasing stakeholder impact from compliance with regulations and the influence of technology.The authors used a quantitative research design, analyzing data from surveys, interviews, and secondary data from financial databases and academic literature. Statistical methods, including correlation and regression analyses, were used to examine the relationship between risk metrics and financial performance among several participants in financial markets. The results suggest movement towards data-driven risk management, given the number of risk management systems incorporating VaR and CVaR models across institutions. The research also reveals that financial firms are more closely aligning risk governance structures with the changing environment of regulations. This research contributes to the literature by offering an integrated perspective on modern risk management practices. It emphasizes the role of regulation and technology as key drivers for effective risk management and highlights organizational resilience as a crucial implication for both researchers and practitioners operating within the complex dynamics of financial markets.

Looking at crisis-induced market behavior in Asia-Pacific, (Kusumah, Asri, Setiawan, & Setiyono, 2022) investigate the time-varying dependencies of Asia-Pacific equity markets during two global crises: the Asian financial crisis (1997-1998) and the subprime mortgage crisis (2007-2009). Their study considers the implications for market linkages across markets and whether differences in the characteristics and origin of the shocks influenced these linkages and developed regional linkages.

They utilize time-series data constructed from MSCI equity market monthly returns for the Asia-Pacific region and the United States, along with panel data for the respective markets. They use different techniques, including vector autoregression (VAR), Granger causality tests, and impulse response functions, to analyze the direction and strength of causal relationships across different markets during the crisis periods analyzed.

The results show that during the Asian financial crisis, predominantly unidirectional causal relationships existed, particularly among emerging markets, illustrating a segmented, reactive market structure. In contrast, the subprime mortgage crisis led to more bidirectional causality with broader connections, particularly in developed markets, showing less segmentation and greater financial integration. The paper highlights how the origin of financial shocks and the rate of market development can influence the degree of interdependence across these multiple markets.

The contributions of this paper are comparative in examining the contagion effects driven by crisis shocks and the incorporation of the level of market integration and the origin of the financial shock in determining inter-market linkages, thus impacting inter-market structural differences.

Complementing this with a focus on post-crisis integration, (Nasir & Du, 2017) examine the effects of the Global Financial Crisis (2008) on financial market integration, specifically in relation to the UK financial sector. The authors are primarily interested in understanding how global financial markets are moving in the post-crisis context, and what that specifically means for the UK market. Using a Panel Vector Autoregressive (VAR) model, the authors assess monthly data from nine different countries from January 2003 to October 2015, focusing on stock, bond, and foreign exchange markets. To account for structural breaks and changes in relationships, the Chow test is used to assess whether the financial markets' engagement with the UK market has changed after the crisis. The findings indicate that there was a substantial change in the engagement of global financial markets, relative to the UK financial sector, post-2008. Developing economies, notably China, Brazil, and India, have influenced the UK financial sector. Moreover, the financial sectors of Germany and the USA have become more competitive relative to the UK financial sector in the time since the crisis, signaling altered relative power positions in global financial markets. This work contributes to the body of literature on financial crises and integration by providing evidence through econometric analysis of shifts in financial market integration after the crisis.

Finally, evaluating risk estimation models in emerging contexts, (Todorova, 2009) examines the effectiveness of Value at Risk (VaR) models for estimating market risk in emerging markets, specifically Bulgaria and Romania, for which it considers models initially developed for more mature markets. The author uses rigorous backtesting methods, specifically Kupiec’s test and Christoffersen’s Markov test, to test a number of different VaR models which include parametric methods based on Normal and Student-t distributions, the Generalized Pareto Distribution, and non-parametric historical simulations. The empirical analysis utilizes the SOFIX index for Bulgaria, the BET index for Romania, and the ATG index for Greece during two time periods: a relatively calm period between 2004 - 2007, and in 2008, which was a volatile year.

The findings indicate that VaR models using a Student-t conditional distribution assumption and Exponentially Weighted Moving Average (EWMA) to estimate variance displayed the highest accuracy in predicting extreme market losses, and, intriguingly, all three countries demonstrated similar performance in backtesting, thereby suggesting that VaR's accuracy is not influenced by market development.

Todorova's research contributes meaningfully to the literature on risk management in emerging markets. By critically evaluating the adaptability of traditional VaR models in less mature financial systems and incorporating crisis-period data, the study provides valuable insights into model robustness and regional risk estimation practices.

The previous studies can be presented in the following table:

Table 1: Summary of Previous Studies.

Title of the Study	Author(s)	Sample Studied	Study Period	Model Used	Key Findings
Banking Networks, Systemic Risk, and the Credit Cycle in Emerging Markets	Sanjiv R. Das ,Madhu Kalimipalli ,Subhankar Nayak (2022)	1,048 financial institutions from 23 emerging markets and 369 U.S. institutions	2004-2016	Systemic risk decomposition , Granger causality, VAR	There is regional heterogeneity in systemic risk across emerging markets, with globalization contributing to stability but not triggering significant risk spillovers.
Downside Risk in Emerging Markets	Yigit Atilgan, K. Ozgur Demirtas (2013)	Aggregate stock market returns from multiple emerging and developed markets.	January 1973 - January 2011	VaR (parametric & nonparametric) , panel regressions	Finds a strong relationship between downside risk and expected returns in emerging markets, which weakens in developed markets.
Downside Risk Measuremen: Expected Shortfall	Issam S. Strub, Edward D. Baker (2011)	MSCI Emerging Markets Index	January 2000 - August 2010.	EVT, GPD, ES, VaR	Concludes that Expected Shortfall (ES) is a more effective risk metric than Value at Risk (VaR) for managing downside risk in emerging

					market equities.
A Value-at-Risk Modeling Techniques to Computing Equity Trading Risk Exposure in Emerging Stock Markets	Mazin A. M. Al Janabi (2021)	Moroccan stock market data	Not specified	VaR, matrix algebra, stress testing	VaR models adapted to low-liquidity markets improve risk control, applicable for emerging markets like Morocco.
Financial development and dynamic investment behavior: Evidence from panel VAR	Inessa Love, Lea Zicchino (2006)	Firm-level data from 36 countries	Various years, focusing on financial development differences	Panel VAR	Financial constraints impact investment more in countries with less developed financial systems. Stronger financial development leads to better capital allocation and growth.
Measuring Dynamic Connectedness with Large Bayesian VAR Models	Dimitris Korobilis Kamil Yilmaz, (2018)	35 U.S. & European financial institutions	2 January 2004- 22 July 2016	Time-Varying Parameter Vector Autoregression (TVP-VAR)	TVP-VAR model captures abrupt turning points in financial markets better than rolling-window VAR. More effective in forecasting systemic financial risks.

Examine Current Trends and Emerging Methodologies in Risk Management Practices Within Financial Markets	Abdul Rahman, Ratna Sari (2023)	Survey/interview & financial data from market participants	Not specified	VaR, CVaR, regression, correlation	Increasing use of Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). AI and blockchain improve risk accuracy and transparency. Compliance is crucial for risk mitigation.
The relationship between asia pacific markets during the financial crisis: var-granger causality analysis	Hayun Kusumah, Marwan Asri, Kusdhianto Setiawan, Bowo Setiyono (2022)	MSCI monthly returns for Asia-Pacific and U.S. markets	1997–1998 (Asian crisis), 2007–2009 (subprime crisis)	VAR, Granger causality, impulse response	Shows that the 1997-98 Asian financial crisis had unidirectional market linkages, while the 2007-09 subprime crisis resulted in bidirectional causality and greater integration.
Integration of Financial Markets in Post Global Financial Crises and Implications for British Financial Sector: Analysis Based on A Panel VAR Model	MuhammadAli Nasir , Min Du (2022)	UK, USA, Germany, China, Brazil, India, and others	Jan 2003 – Oct 2015	Panel VAR, Chow test	Finds that post-2008, global financial market engagement with the UK changed, with developing markets gaining influence and competition rising from

					Germany and the USA.
avaliação da performance de modelos de value-at-risk em mercados emergentes: uma aplicação aos mercados da bulgária e da roménia	Darina Todorova (2009)	Bulgaria, Romania, Greece (SOFIX, BET, ATG indices)	2000–2008 (split into 2004–2007 and 2008)	VaR (Normal, Student-t), EWMA, backtesting	Demonstrates that VaR models, especially with a Student-t distribution and EWMA, provide accurate risk estimates in emerging markets like Bulgaria and Romania.

Newly established financial markets create new challenges for risk management due to volatility, structural deficiencies, and integration into the global economy. At times, standard risk models relied upon to develop strategies do not adequately reflect the realities of these conditions. The studies reviewed focus on systemic risk, downside risk, and the limitations of standard VaR models, while highlighting the utility of Expected Shortfall and various contextual adaptations of VaR. The research demonstrates that emerging economies need customized frameworks to improve their financial stability.

Empirical study

Risk management constitutes one of the essential pillars of the modern financial system and is a key component of the stability and resilience of institutions and markets, in an increasingly interconnected global economy, exposure to multiple sources of financial risk such as market risk, credit risk, and liquidity risk has grown exponentially. At the same time, it is imperative for all market participants to have the ability to identify, evaluate, and adopt processes for effective risk mitigation to protect the ongoing viability of their assets and to maintain investor confidence.Effectively measuring and managing risk is more than a utility for individual investors, it is key to the overall stability of the financial system, especially during periods of financial turbulence.

Value-at-Risk (VaR) has become the predominant measure of financial risk by evaluating the largest possible loss at a given confidence level over a specified time horizon. It is widely used across banking, investment, and portfolio management. While the basic concept of VaR is simple, its validity depends on the underlying model and its assumptions about return distributions and volatility.

A fundamental approach to quantifying market risk often involves the Value-at-Risk (VaR) framework. Under the simplifying assumption of constant volatility (σ), VaR estimates the maximum potential loss over a given time horizon at a specified confidence level. This parsimonious specification of VaR serves as a useful starting point for risk assessment.

However, the inherent complexities and evolving nature of emerging market dynamics can sometimes challenge the assumptions underpinning simpler risk models. Empirical analysis might reveal patterns in the data that suggest a more nuanced characterization of risk is warranted. This observation naturally leads to a broader consideration of alternative methodologies capable of capturing the intricate features of financial time series in these markets.

Building upon the foundation laid in Chapter one, this chapter continues the exploration of risk management using the same dataset, estimation periods, and forecasting horizons. Python 3.13[1] and OxMetrics are employed.

1. Overview of the data:

In this chapter, we build on the information in Chapter One, where we look at the daily closing prices of the iShares ETF on MSCI Emerging Markets (symbol: EEM) from April 23, 2003, to September 24, 2024. The analysis is quantitative, focusing on statistical methods for time series analysis. The data will be separated into an estimation period from April 23, 2003, to March 24, 2024, and a forecast period from March 25, 2024, to September 24, 2024. All statistical analyses were conducted using Python version 3.13 and OxMetrics version 7.2.

2. Methodology:

This section presents the models used to estimate Value at Risk (VaR), focusing on the parametric model and the GJR-GARCH model. It also discusses the evaluation of model accuracy using backtesting methods such as the Kupiec test and the Dynamic Quantile test.

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[1]**Python:** is a versatile language with powerful tools for statistical analysis, numerical computation, and data visualization. Its ecosystem, including libraries such as NumPy, pandas, and matplotlib, facilitates the manipulation of financial data, rigorous estimation of model parameters, and dynamic visualization of risk metrics.

2.1. Parametric VaR Model:

The parametric method of Value at Risk (VaR) determines VaR from the standard deviation of the investment portfolio's returns. This approach assumes that the distribution of asset returns follows a specific theoretical distribution, which is used to estimate the potential loss in value of a portfolio over a defined period for a given confidence interval.

The parametric VaR is calculated using the following formula:

$$\mathrm{VaR}_{\alpha} = \mu + \sigma \cdot z_{\alpha}$$

Where:

- VaR_{α}: is the Value at Risk at the (α) confidence level.
- μ: is the mean of the returns.
- σ: is the standard deviation of the returns.
- Zα: is the critical value (quantile) from the standard normal distribution corresponding to the chosen confidence level α.

The model calculates VaR for both long and short positions.

For long positions, VaR estimates the maximum potential loss that an investor might incur over a specific holding period at a given confidence level. The relevant quantile is in the left tail of the distribution (e.g., 1% or 5%).

This applies to positions that profit when the underlying asset price increases. For VaR on long positions, we are interested in large negative returns (losses). This section tests the lower tail of the return distribution.

For short positions, VaR estimates the maximum potential loss if the asset price increases. The relevant quantile is in the right tail of the distribution (e.g., 99% or 95%, which correspond to a 1% or 5% loss in the context of a short sale).

This refers to positions that profit when the underlying asset price goes down. For VaR on short positions, we are interested in large positive returns or gains that are unexpected, or large negative losses if the short position isn't perfect (more commonly, it refers to the risk of losing money on a short position if the price goes up significantly - a loss is a positive change in value for a short). However, in this context, "Short positions" often refers to the upper tail of the return distribution, i.e., large positive returns, which could be seen as "unexpected gains" relative to a quantile forecast.

2.2. GJR-GARCH model:

The GJR-GARCH (Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity) model is a popular econometric model used in financial time series analysis to capture volatility clustering and leverage effects (asymmetric impact of positive and negative shocks on volatility).

The GJR-GARCH model is calculated using the following formula:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \left(\alpha_i \epsilon_{t-i}^2\right) + \sum_{i=1}^{q} \left(\gamma_i I_{t-i} \epsilon_{t-i}^2\right) + \sum_{j=1}^{p} \left(\beta_j \sigma_{t-j}^2\right)$$

Where:

- $\boldsymbol{\sigma_t^2}$: The conditional variance at time t. This is what the model seeks to explain and forecast.
- **ω**: The constant term (long-run average variance). It must be positive (ω>0).

- ϵ_{t-i}^2: The squared error terms from previous periods (ARCH terms). These represent past shocks or news.
- σ_{t-j}^2: The conditional variances from previous periods (GARCH terms). The coefficient βj measures the persistence of volatility.
- I_{t-i}: An indicator variable (dummy variable) that takes the value:

  1 if ϵ_{t-i}: <0 (i.e., if there was a negative shock or "bad news" at time t−i).

  0 if ϵ_{t-i}: ≥0 (i.e., if there was a positive or zero shock or "good news" at time t−i).

- γ_i: The coefficient for the asymmetric term. This is the crucial parameter in the GJR-GARCH model.

  If γ_i>0, it indicates the presence of a leverage effect, meaning that negative shocks have a larger impact on subsequent volatility than positive shocks. The total impact of a negative shock on variance is (αi+γi).

  If γ_i=0, the model reduces to a standard GARCH model, as the asymmetric term vanishes.

- **p:** The number of lagged conditional variance terms (GARCH lags).
- **q:** The number of lagged squared error terms (ARCH lags and leverage term lags).

The GJR-GARCH model is extensively used in:

Risk Management: For calculating Value at Risk (VaR) and Expected Shortfall (ES), as it provides more accurate forecasts of volatility, especially during market downturns.

Option Pricing: Where volatility is a key input.

Portfolio Allocation and Hedging: To make informed decisions based on expected future volatility.

Financial Market Analysis: To understand the dynamics of asset price movements and the impact of news.

2.3. VaR Backtesting:

To assess the accuracy of the VaR model, backtesting is performed. Backtesting involves comparing the VaR estimates generated by the model with the actual realized profits and losses. If the model is accurate, the number of "exceptions" (instances where actual losses exceed the VaR estimate) should be consistent with the chosen confidence level.

2.3.1 Kupiec LR test:

One of the primary tests used in this analysis is Kupiec's Likelihood Ratio (LR) test for unconditional coverage. This test evaluates whether the observed frequency of exceptions is statistically consistent with the expected frequency based on the VaR model's confidence level (α). It does not consider the timing of exceptions, only the total number.

The LR statistic is calculated as:

$$LR_{uc} = -2\ln\left(\frac{(1-\alpha)^{N-x}\alpha^x}{(1-\hat{p})^{N-x}\hat{p}^x}\right)$$

Where:

- **N:** is the total number of observations.
- $\boldsymbol{x}$: is the number of exceptions.
- $\boldsymbol{\alpha}$: is the VaR confidence level.
- $\widehat{\boldsymbol{p}} = x$ /N is the observed failure rate.

Hypotheses:

- **H_0 (Null Hypothesis):** The VaR model is accurate, meaning the observed proportion of exceptions is equal to the specified VaR level (α).
- **H_1 (Alternative Hypothesis):** The VaR model is inaccurate, meaning the observed proportion of exceptions is significantly different from the specified VaR level.

Rule: If the P-value is less than a chosen significance level (commonly 0.05), you reject the null hypothesis. The null hypothesis for Kupiec is that the actual number of exceptions is consistent with the VaR confidence level.

2.3.2 Dynamic Quantile Test:

The Dynamic Quantile (DQ) test, proposed by Robert Engle and Simone Manganelli in 2004, is a more comprehensive method for backtesting Value at Risk (VaR) models compared to the unconditional coverage test of Kupiec. While Kupiec's test only examines whether the overall number of exceptions is correct, the DQ test additionally assesses whether these exceptions are independent of each other and not clustered, thereby testing for conditional coverage. This is crucial because a good VaR model should not only predict the correct number of breaches on average but also predict them at the right times.

The DQ test statistic is typically formulated as a Wald test or a Likelihood Ratio test. For the Wald test, the statistic is:

$$DQ = \frac{\hat{\beta}'X'(X'X)^{-1}X\hat{\beta}}{\alpha(1-\alpha)}$$

Where:

- $\widehat{\boldsymbol{\beta}}$: is the vector of estimated regression coefficients.
- $\boldsymbol{X}$: is the matrix of explanatory variables (including an intercept).

Hypotheses:

- **H_0 (Null Hypothesis):** The VaR model is correctly specified.
- **H_1 (Alternative Hypothesis):** The VaR model is misspecified.

Rule: If the P-value is less than a chosen significance level (commonly 0.05), you reject the null hypothesis. The null hypothesis for the DQ test is that the exceptions are independent and correctly specified by the model.

3. Results and discussion:

This section presents results from applying different Value at Risk (VaR) models to the EEM ETF data during the estimation period. The evaluation focuses on the models' performance based on statistical tests, highlighting the importance of selecting models that provide accurate and reliable risk estimates.

3.1 First Step: Parametric VaR Model and In-Sample Backtesting Results for the Estimation Period.

The parametric VaR model was backtested over the estimation period (April 24, 2003, to March 24, 2024), which consists of 5265 observations.

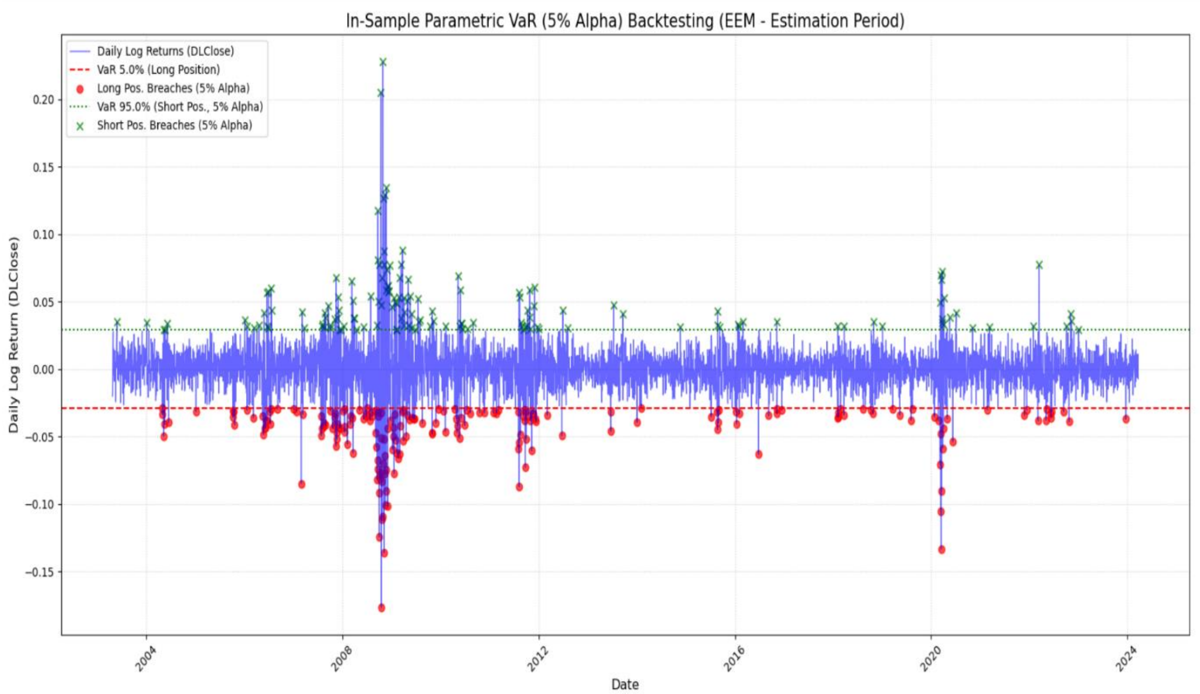
The estimation period statistics for the EEM (MSCI) Returns are:

- **Mean Return (μ):** 0.000238
- **Standard Deviation of Return (σ):** 0.017569

These values are used as inputs for the parametric VaR calculation.

$$\mathrm{VaR}_{\alpha} = 0.000238 + 0.017569 \cdot z_{\alpha}$$

Figure (1): In-Sample Parametric VaR (5% Alpha) Backtesting (EEM - Estimation Period)



Source: Outputs of the Python 3.13

The plot visually represents the backtesting of the parametric VaR model for the EEM ETF from approximately 2003 to 2024. The blue line tracks the daily log returns, exhibiting distinct periods of fluctuating volatility, with notable spikes during the 2008 financial crisis and the early 2020 COVID-19 pandemic.

Two VaR levels are depicted: a red dashed line shows the 5% VaR for long positions (a negative value indicating maximum expected loss), and a green dashed line shows the 95% VaR for short positions (a positive value indicating maximum loss for a short seller). Breaches of these VaR estimates are marked as red circles for long positions (when actual losses exceeded the VaR) and green 'x' markers for short positions (when actual gains/short seller losses exceeded the VaR).

The table presents the backtesting results of the parametric VaR model for both long and short positions, using the Kupiec and Dynamic Quantile tests at different confidence levels (1% and 5% for long positions, 95% and 99% for short positions), showing the number of exceptions and the corresponding test statistics.

Table 1: The backtesting results of the parametric VaR model for both long and short position

Position	Quantile	Test	Exceptions	Total Obs	Statistic	P-value
Long	0.01	Kupiec LR	84	5265	15.970230	6.434644e-05
Long	0.01	Dynamic Quantile	84	5265	NaN	NaN
Long	0.05	Kupiec LR	202	5265	16.253080	5.541944e-05
Long	0.05	Dynamic Quantile	202	5265	NaN	NaN
Short	0.99	Kupiec LR	70	5265	5.233876	2.215111e-02
Short	0.99	Dynamic Quantile	70	5265	NaN	NaN
Short	0.95	Kupiec LR	147	5265	63.875735	1.332268e-15
Short	0.95	Dynamic Quantile	147	5265	NaN	NaN

Source: Outputs of the Python 3.13

3.1.1 Kupiec LR test (Long Positions):

Quantile: 1.0% (Alpha = 0.01)

- **Expected Exceptions:** With a 1% VaR and 5265 observations, the model would predict, on average, 5265·0.01=52.65 exceptions.
- **Observed Exceptions:** The model recorded 84 exceptions.
- **Kupiec LR Statistic:** 15.970230
- **P-value:** 0.0001 (or 6.434644e-05 from the summary table)

Conclusion (at 5% significance level):

Since the p-value (0.0001) is less than the significance level (0.05), we reject the null hypothesis (H0). This indicates that the VaR model is inaccurate at the 1% confidence level for long positions. The observed number of exceptions (84) is significantly higher than the expected number (52.65), suggesting the model underestimates risk at this quantile.

Quantile: 5.0% (Alpha = 0.05)

- **Expected Exceptions:** With a 5% VaR, the model would predict 5265·0.05=263.25 exceptions.
- **Observed Exceptions:** The model recorded 202 exceptions.
- **Kupiec LR Statistic:** 16.253080
- **P-value:** 0.0001 (or 5.541944e-05 from the summary table)

Conclusion (at 5% significance level):

the p-value (0.0001) is less than 0.05. Therefore, we reject the null hypothesis (H0). The VaR model is also deemed inaccurate at the 5% confidence level for long positions. In this case, the observed number of exceptions (202) is significantly lower than the expected number (263.25), suggesting the model overestimates risk (i.e., it is too conservative) at this quantile.

3.1.2 Kupiec LR test (Short Positions):

Quantile for VaR: 99.0% (Effective Alpha for loss = 1.0%)

- **Expected Exceptions:** With an effective alpha of 1%, the model expects $5265 \cdot 0.01 = 52.65$ exceptions.
- **Observed Exceptions:** The model recorded 70 exceptions.
- **Kupiec LR Statistic:** 5.233876
- **P-value:** 0.0222 (or 2.215111e-02 from the summary table)

Conclusion (at 5% significance level):

The p-value (0.0222) is less than 0.05. Thus, we reject the null hypothesis (H0). The parametric VaR model is inaccurate for short positions at an effective 1% loss level. The observed number of exceptions (70) is higher than expected (52.65), indicating the model underestimates risk for short positions at this quantile.

Quantile for VaR: 95.0% (Effective Alpha for loss = 5.0%)

- **Expected Exceptions:** With an effective alpha of 5%, the model expects $5265 \cdot 0.05 = 263.25$ exceptions.
- **Observed Exceptions:** The model recorded 147 exceptions.
- **Kupiec LR Statistic:** 63.875735
- **P-value:** 0.0000 (or 1.332268e-15 from the summary table)

Conclusion (at 5% significance level):

The p-value is extremely small (effectively 0) and much less than 0.05. We reject the null hypothesis (H0). The model is highly inaccurate for short positions at an effective 5% loss level. The observed number of exceptions (147) is significantly lower than the expected number (263.25), suggesting the model overestimates risk (is too conservative) for short positions at this quantile

3.1.3 Dynamic Quantile Test (Long Positions and Short Positions):

The Dynamic Quantile test, which assesses both unconditional and conditional coverage (i.e., independence of exceptions), could not be successfully performed for any of the scenarios. The output indicated Test not performed (NaN). Further diagnostic information revealed that the internal logistic regression used by the DQ test failed due to encountering a singular matrix, attributed to a data variance problem. This often occurs when the proportion of exceptions is very close to 0 or 1, or when there is insufficient variation in the data for stable estimation, particularly in cases of extreme imbalance between exceptions and non-exceptions within the computational window of the test. Consequently, no conclusions about the conditional coverage of the VaR model could be drawn from this test.

Overall Conclusion:

The backtesting results consistently demonstrate that the simple parametric VaR model, assuming a normal distribution of returns, is inadequate for accurately estimating Value at Risk for the EEM ETF over the analyzed period. Kupiec's LR test rejected the model's accuracy for all tested quantiles and positions at the 5% significance level. The model either underestimated or overestimated risk depending on the specific quantile and position type. The inability to perform the Dynamic Quantile test, due to numerical issues arising from data characteristics in the context of the test's internal calculations, prevents an assessment of the conditional coverage properties of the model.

These findings strongly suggest the inadequacy of the simple parametric VaR model and highlight the need to employ more sophisticated methodologies. Therefore, will proceed to implement and evaluate Value at Risk models based on the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework. GARCH models are well-suited to address the observed shortcomings, as they explicitly account for time-varying volatility and can be combined with distributions capable of capturing non-normality in returns (such as the Student's t-distribution). The successful implementation and rigorous backtesting of these GARCH-based VaR models are anticipated to provide a more robust and reliable risk management framework for the EEM ETF, better reflecting its dynamic risk characteristics.

3.2 Second Step: VaR Estimation Based on ARMA-GARCH.

Given the shortcomings of the simple model, particularly its failure to address time-varying volatility, we evaluate the in-sample performance of the ARMA(2,1)-GARCH(1,2) model used in the first chapter to measure market risk through Value at Risk (VaR). Unlike out-of-sample forecasting, we do not perform volatility predictions in this chapter. Instead, we assess how well the model explains the risk within the sample period by applying VaR backtesting techniques. The main goal of these tests is to determine whether the number of times actual losses exceed the calculated VaR, commonly known as violations, is consistent with theoretical expectations at given confidence levels.

The table presents the Kupiec LR test results for long and short positions at various confidence levels, showing success or failure rates, test statistics, and p-values to evaluate the accuracy of the VaR model. This is part of the In-sample Value-at-Risk Backtesting. The following table details these results.

Table 2: The Kupiec LR Test (ARMA (2,1)-GARCH (1,2)).

Kupiec LR test: Short positions			
Quantile	**Success rate**	**Kupiec LRT**	**P-value**
0.95000	**0.95228**	**0.58485**	**0.44442**
0.97500	**0.97719**	**1.0621**	**0.30273**
0.99000	**0.99011**	**0.0069394**	**0.93361**
0.99500	**0.99544**	**0.20829**	**0.64811**
0.99750	**0.99715**	**0.24951**	**0.61742**
Kupiec LR test: Long positions			
Quantile	**Failure rate**	**Kupiec LRT**	**P-value**
0.050000	**0.050760**	**0.063733**	**0.80069**
0.025000	**0.027567**	**1.3764**	**0.24072**
0.010000	**0.011407**	**1.0059**	**0.31588**

0.0050000	**0.0053232**	**0.10814**	**0.74227**
0.0025000	**0.0022814**	**0.10389**	**0.74721**

Source: Outputs of the Oxmetrics 7.2

3.2.1 Kupiec LR test (Short positions):

The Kupiec LR test for short positions indicates strong model performance. At the 0.95 and 0.99 quantiles, the actual success rates were 95.228% and 99.011%, respectively, closely matching the expected levels. The p-values for all quantiles (0.44442, 0.30273, 0.93361, 0.64811, 0.61742) are above the 0.05 threshold, indicating no statistically significant difference between the expected and actual violations. Therefore, the Kupiec test is passed for all tested VaR levels in short positions. The actual frequency of returns exceeding the upper VaR limits is statistically consistent with the model's predictions.

3.2.2 Kupiec LR test (Long Positions):

The Kupiec test results for long positions demonstrate strong model performance. At the 0.05 and 0.01 quantiles (corresponding to 95% and 99% VaR for losses), the actual failure rates were 5.076% and 1.1407%, respectively, closely aligning with expected values. The p-values from the Kupiec Likelihood Ratio Test, all well above 0.05, indicate no statistically significant difference between expected and observed violations. Therefore, the model passes the Kupiec test for all tested VaR levels in long positions.

Kupiec LR test Conclusion: the Kupiec test confirms that the model accurately predicts the frequency of VaR breaches for both short and long positions across different confidence levels. While this supports the model's validity, it represents only one aspect of its overall performance.

This table shows the application of the Dynamic Quantile test for both short and long positions across different confidence levels. The test is used to assess the conditional accuracy and adequacy of the VaR model as part of the in-sample backtesting process.

Table 3: The Dynamic Quantile Test (ARMA (2,1)-GARCH (1,2)).

Dynamic Quantile Test: Short positions		
Quantile	**Stat.**	**P-value**
0.95000	**13.848**	**0.031377**
0.97500	**2.5162**	**0.86665**
0.99000	**2.6684**	**0.84916**
0.99500	**0.71668**	**0.99412**
0.99750	**0.50929**	**0.99772**
Dynamic Quantile Test: Long positions		
Quantile	**Failure rate**	**P-value**
0.050000	**10.667**	**0.099241**

0.025000	**20.748**	**0.0020359**
0.010000	**15.871**	**0.014463**
0.0050000	**15.613**	**0.015987**
0.0025000	**32.225**	**1.4774e-005**

Source: Outputs of the Oxmetrics 7.2

3.2.3 Dynamic Quantile Test (Long Positions and Short Positions):

The Dynamic Quantile (DQ) test reveals mixed model performance. For short positions, it fails at the 95 percent VaR level, with a p-value of 0.031377, suggesting potential clustering of extreme positive returns. However, it succeeds at the higher confidence levels of 97.5 percent, 99 percent, 99.5 percent, and 99.75 percent, as the corresponding p-values are well above 0.05. In contrast, for long positions, the test passes only at the 95 percent level, with a p-value of 0.099241, but fails at all more conservative levels. At these levels, the very low p-values indicate strong statistical rejection. These findings suggest that while the total number of exceptions may align with expectations under the Kupiec test, they are not independently distributed. This pattern of clustering indicates that the model may fall short in capturing volatility dynamics, particularly during periods of elevated market stress.

Dynamic Quantile Conclusion: This test reveals a significant weakness in the model, particularly for the lower tail (losses on long positions) at commonly used VaR levels. The model fails to capture the time-varying nature of risk or volatility, leading to clustered exceptions.

Overall Conclusion:

The ARMA(2,1)-GARCH(1,2) model demonstrated strong performance in terms of coverage accuracy, as it successfully passed the Kupiec test for both long and short positions across all examined VaR levels. However, the results of the Dynamic Quantile (DQ) test revealed dynamic shortcomings. The clustering of violations suggests that the model does not fully capture the time-varying nature of risk, especially during periods of heightened market volatility.

3.3 Third Step: VaR Estimation Based on the Best-Fit Model.

Given the importance of asymmetries in financial returns, particularly the leverage effect where negative shocks tend to increase volatility more than positive shocks of equal magnitude, and the importance of accurately estimating Value-at-Risk (VaR), we tested several models to identify the best fit. We found that the ARMA(2,1)-GJR-GARCH(2,1) model is the most suitable, as it successfully passed backtesting procedures, confirming its reliability in forecasting VaR. This model effectively accounts for asymmetries in returns, improving the precision of VaR estimates compared to symmetric models.

Table 4: The Kupiec LR Test (ARMA(2,1)-GJR-GARCH(2,1)).

Kupiec LR test: Short positions			
Quantile	**Success rate**	**Kupiec LRT**	**P-value**
0.95000	**0.94962**	**0.015971**	**0.89943**
0.97500	**0.97567**	**0.096382**	**0.75622**

0.99000	**0.98935**	**0.21740**	**0.64102**
0.99500	**0.99487**	**0.018562**	**0.89163**
0.99750	**0.99696**	**0.57889**	**0.44675**
Kupiec LR test: Long positions			
Quantile	**Failure rate**	**Kupiec LRT**	**P-value**
0.050000	**0.047148**	**0.91724**	**0.33820**
0.025000	**0.025475**	**0.048449**	**0.82578**
0.010000	**0.0098859**	**0.0069394**	**0.93361**
0.0050000	**0.0039924**	**1.1534**	**0.28284**
0.0025000	**0.0015209**	**2.3534**	**0.12501**

Source: Outputs of the Oxmetrics 7.2

3.3.1 Kupiec LR test (Short positions and Long Positions):

The Kupiec LR test results indicate strong performance for the model in terms of unconditional coverage for both short and long positions. For short positions, across all tested quantiles (0.95000 to 0.99750), the P-values were consistently high (ranging from 0.44675 to 0.89943), well above the 0.05 significance level. This suggests that the observed success rates are statistically in line with the expected quantiles. Similarly, for long positions, at all corresponding failure rate quantiles (0.050000 to 0.0025000), the P-values were also substantially greater than 0.05 (ranging from 0.12501 to 0.93361). This implies that the observed number of failures aligns with the expected number of failures. Therefore, the model successfully passes the unconditional coverage test, meaning the frequency of exceptions is consistent with the chosen confidence levels.

3.3.2 Dynamic Quantile Test (Short positions and Long Positions):

Table 5: The Dynamic Quantile Test (ARMA(2,1)-GJR-GARCH(2,1)).

Dynamic Quantile Test: Short positions		
Quantile	**Stat.**	**P-value**
0.95000	**6.6514**	**0.35430**
0.97500	**2.2383**	**0.89653**
0.99000	**2.4056**	**0.87888**
0.99500	**0.75337**	**0.99327**
0.99750	**0.92093**	**0.98843**
Dynamic Quantile Test: Long positions		

Quantile	Failure rate	P-value
0.050000	7.6922	0.26153
0.025000	5.6775	0.46027
0.010000	6.1762	0.40374
0.0050000	9.4650	0.14906
0.0025000	2.0594	0.91415

Source: Outputs of the Oxmetrics 7.2

The Dynamic Quantile (DQ) test results demonstrate that the model also performs well regarding conditional coverage, for both short and long positions, indicating that exceptions are not only correctly numbered but also independently distributed over time. For short positions, across all quantiles, the P-values were very high (ranging from 0.35430 to 0.99327), far exceeding the 0.05 threshold. This supports the hypothesis that exceptions are both unconditionally correct and independent. For long positions (assuming "Failure rate" under DQ is the test statistic), the P-values were also consistently well above 0.05 across all tested quantiles (ranging from 0.14906 to 0.91415). This suggests that, for long positions as well, the model's exceptions are correctly specified and not clustered, fulfilling the criteria for conditional coverage.

Overall Conclusion:

The ARMA(2,1)-GJR-GARCH(2,1) model model successfully passed both the Kupiec LR and the DQ backtesting procedures, indicating its adequacy in capturing extreme quantile behavior and in producing forecasts consistent with observed exception rates. This represented a significant improvement over previous specifications and supported the model’s use for practical Value-at-Risk (VaR) estimation.

3.3.3 Diagnostic Evaluation and Limitations of the ARMA(2,1)-GJR(2,1) Model:

Despite its success in backtesting, the ARMA(2,1)-GJR-GARCH(2,1) model presented concerns regarding the autocorrelation of squared standardized residuals, as reflected in the Q-statistics. Specifically, at lags 5, 10, and 50, the p-values fell below the conventional 5% significance threshold, suggesting the presence of remaining ARCH effects:

Table 6: Box-Pierce Q-Statistics on (Squared data) Test.

Degree of lag	Value	P-value
Q (5)	6.66432	0.0357158
Q (10)	14.7637	0.0391507
Q (20)	19.7075	0.2894620
Q (50)	65.2974	0.0397895

Source: Outputs of the Oxmetrics 7.2

These results suggest that while the ARMA(2,1)-GJR-GARCH(2,1) model improves upon previous attempts in terms of quantile coverage and risk forecasting, it may not fully eliminate all second-order dependencies in the conditional variance structure. However, it is important to contextualize these diagnostic results. First, the p-values are marginally below the threshold, indicating only modest evidence of misspecification. Second, the primary goal, achieving reliable VaR estimates through validated backtesting, was attained. Therefore, the model remains defensible for applied risk management purposes.

Moreover, the tension between satisfying quantile-based backtests and passing residual diagnostics is well-documented in the literature. In practice, trade-offs are often necessary, and models that perform exceptionally well in one domain may underperform in another. As such, the selected ARMA(2,1)-GJR-GARCH(2,1) model represents a pragmatic and academically grounded compromise.

Chapter conclusion:

This chapter assessed Value-at-Risk (VaR) models using actual emerging market data. While some of the simple parametric models were ruled out as inadequate, the ARMA-GARCH model improved unconditional coverage but showed weaknesses in the Dynamic Quantile (DQ) test, indicating clustered exceptions. Ultimately, the ARMA-GJR-GARCH model proved to be the most effective option, successfully passing both the Kupiec LR test and the DQ test, and capturing asymmetries and time-varying volatility. Although there were some concerns regarding the relatively weak presence of ARCH effects in the squared standardized residuals, the model's backtesting results confirmed its practical effectiveness. We were able to verify that the model provides valid VaR estimates for risk management purposes.

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Concluding Chapter : Forecasting Accuracy Between Traditional Econometric and AI Models

Chapter Introduction

Volatility is a central concept in the financial market since it reflects how much prices vary and the level of uncertainty. Good volatility forecasting and sound modeling methods are essential for many financial applications such as risk management, derivative pricing, portfolio optimization, and the generation of trading strategies.

Over the past few years, traditional models such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Value at Risk (VaR) model have been widely used to predict volatility and manage risk, often with reasonably good results. However, trust in these models is gradually diminishing due to inherent limitations, such as assumptions of stationarity and normally distributed returns in some implementations, which often do not hold in real-world scenarios, particularly in emerging markets.

Emerging markets are less mature than developed economies, are more volatile, and may have less well-defined financial infrastructure. Therefore, these markets pose a set of forecasting and risk management opportunities and challenges. Traditional forecasting models are not usually capable of detecting the nonlinear dynamics, as well as identifying structural breaks common in emerging markets. AI models, and models that utilize deep learning architectures (LSTM, CNN, etc.), have strong conceptual support for uncovering hidden patterns in emerging markets, as well as adapting to new regimes and the potential for making better forecasts.

The use of AI techniques in capital markets is not a recent phenomenon. Over the years, these techniques have been gradually integrated into various financial functions. Market intermediaries and asset managers have employed them in areas such as advisory services, portfolio management, and risk management.

In recent years, AI technologies have witnessed remarkable advancements in terms of innovation, investment, and practical interest. As market participants continue to explore and expand the applications of these technologies, the role of AI in capital markets is expected to grow even further.

This chapter contributes by presenting a comparative analysis between traditional approaches, specifically the GARCH model and the Value at Risk (VaR) measure, and AI-based techniques within the context of emerging markets. The preceding chapters have laid the foundation for this analysis by exploring volatility forecasting using GARCH models and risk management through VaR[2].

[2] **Note:** in econometrics literature VAR is vectorial autoregressive and the value at risk is written VaR.

1. Definition of Artificial Intelligence and Financial Forecasting:

Initial applications of Artificial Intelligence (AI) and Machine Learning (ML) in finance date back to the 1980s, and their roles have evolved to include complex tasks like price forecasting and fraud detection . AI and ML have also begun to revolutionize the financial sector through the enhancement of decision-making processes, the automation of tasks, the and personalization of services. A study by the World Economic Forum (2018) suggests that the financial sector's integration of these technologies could lead to an added value of a trillion dollars by 2025 (Hajj & Hammoud, 2013).

Artificial Intelligence (AI) is a field of computer science aimed at developing systems and software capable of simulating human behavior and performing tasks that require human intelligence, such as learning, reasoning, decision-making, and problemsolving. Since its inception in the mid-20th century, AI has undergone tremendous advancements, evolving from a mere concept in science fiction to an integral part of daily life and industrial operations (Shawaqfeh, 2025).

Artificial Intelligence (AI) is defined as a set of technologies that enable machines to perform complex tasks that typically require human thinking, learning, and interaction. In the context of financial forecasting, AI can be used to analyze historical data, identify patterns, and make predictions about future market behavior. This can include predicting stock prices, credit risk, and other financial metrics (Shawaqfeh, 2025).

One of the key concepts in AI-powered financial forecasting is machine learning, which involves training algorithms on large datasets to make predictions or classify outcomes. Machine learning algorithms can be trained on a variety of data sources, including historical financial data, economic indicators, and news articles (Shawaqfeh, 2025).

2. The Role of AI in Financial Forecasting:

Artificial Intelligence (AI) is changing the game in financial forecasting. It is transforming how organizations evaluate risk and make forecasts. Conventional methods, which rely primarily on a linear approach coupled with historical data, are no longer suitable for evaluating risk and forecasting in today's integrated and unpredictable markets. AI can analyze vast datasets and complex patterns to provide a more powerful alternative that improves forecasting accuracy and supports better decision making. In the following items, we will explain the role of AI in financial forecasting (Yousaf, 2022):

Machine Learning in Financial Forecasting: One of the primary advantages of AI in financial forecasting is its capacity for machine learning. Machine learning algorithms can automatically learn from historical data, allowing them to improve their predictive capabilities over time without explicit programming. For instance, algorithms can be trained on past financial data to recognize patterns associated with economic downturns, enabling organizations to anticipate similar events in the future. This dynamic learning process not only enhances the accuracy of forecasts but also helps in identifying emerging trends that may not be evident through traditional methods.

Incorporating Diverse Data Sources: Moreover, AI-driven predictive models can incorporate a wide array of data sources, including structured and unstructured data, to refine forecasting outcomes. This includes not only historical financial data but also real-time market information, news sentiment analysis, social media trends, and macroeconomic indicators. By synthesizing this diverse range of information, AI can generate more holistic and nuanced forecasts. For example, integrating social media sentiment into forecasting models can help predict consumer behavior and market reactions, providing valuable insights for organizations seeking to make timely decisions.

Improving Risk Assessment: Another significant aspect of AI in financial forecasting is its ability to improve risk assessment processes. Through advanced analytics, AI can identify potential risks that traditional methods may overlook. By employing techniques such as neural networks and ensemble learning, AI models can process complex interdependencies within financial data, allowing organizations to quantify risks with greater precision. This capability is particularly beneficial in stress testing scenarios, where organizations simulate adverse conditions to evaluate their resilience. AI can help refine these simulations by providing more accurate projections of asset behavior under various stress conditions.

Enhancing Speed and Efficiency: Traditional forecasting methods can be time-consuming and labor-intensive, often involving manual data collection and analysis. In contrast, AI automates these tasks, allowing financial analysts to focus on interpreting results and strategizing based on insights generated by AI models. This acceleration not only saves time but also improves the overall agility of organizations in responding to market changes.

may raise legal and ethical concerns related to data privacy, transparency, and accountability.

3. Machine Learning Models:

The machine learning methods described below represent the traditional and most widely used algorithms, not only in financial literature but also across various fields of knowledge. These algorithms are considered foundational in many modern applications, reflecting their flexibility and effectiveness in data analysis and prediction**:** (Zhang, 2024)

3.1. K-Nearest Neighbors (KNN) methods:

The K-Nearest Neighbors (KNN) is a non-parametric method proposed by Cover & Hart (1967). It is one of the most common and straightforward methods in machine learning methods. The KNN concept aims to make it a good tool for classification in different applications. Particularly, it can be used as a local nonlinear model for regression as well.

In the case of regression, the method allows a simple model to be fitted to the neighborhood of the point to be predicted. The neighborhood of a point in KNN model is defined by taking the k values having the lowest values for a chosen distance notation (usually Euclidean distance) defined on the space of the input vector. Similarly, the nearest neighbors of a test point are selected by looking for the k smallest distances between the test point and the training points. Then the prediction for an unknown input vector ($x*$) is computed as follows:

$$y(x^*) = \frac{1}{k} \sum_{i \in KNN} y(x_i).$$

Here, $y(x_i)$ is the output vector based on the ith nearest neighbor of the input vector in the sample. The choice of the optimal number of neighbors (k) will be performed through automatic leave-one-out selection. In a simple word, if the machine receives a sample, the algorithm first searches for its (K) nearest neighbors in the feature space depending on the feature vectors and defined distance. In this case, every data point is represented in the form (x, y) where (x) represents the vector of input values and (y) the corresponding output vector which will usually defined as a forecasting series when doing regression. What is worth to note, the amount of training set data mainly affects the accuracy of the (KNN) which means that the more historical data fed to the machine, the more accurate result will be get.

3.2. Artificial Neural Network (ANN) method:

In machine learning, an artificial neural network (ANN) is a network of interconnected elements, which are called neurons. Neural networks are non-linear and non-parametric models that have their roots in biology. The neurons are used to estimate functions based on the inputs. The neurons are connected by joint mechanism which is consisted of a set of assigned weights. The back propagation training (BP) algorithm is usually used to minimize the quadratic error by descent maximum gradient.

Therefore, the ANN method can be called back propagation neural network (BPNN). The method can be described as follows:

$$\mu_p = \sum_{i=1}^{n} \omega_{p_i} x_i.$$
$$y_p = \varphi\left(u_p + b_p\right).$$

Where:

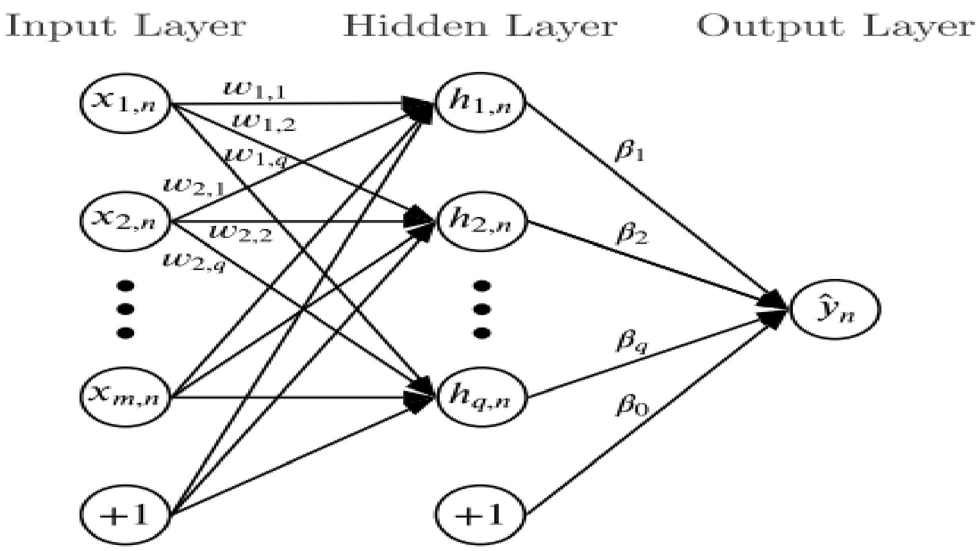
- **(x_i):** is the input data.
- **(ω_{p_i}):** describes the connection weights of neurons.
- **(u_p):** is the input combiner.
- **(b_p)**: is the bias.
- ***(φ):*** is the activation function.
- **(y_p)**: is the output of the neuron.

In ANN works, multi-layer feed forward (MLP) is a common approach which has three layers: input layer, output layer, and hidden layer. Neuron takes the values of inputs parameters, sums them up with the assigned weights, and adds a bias. With the application of transfer function, the outputs which are the forecasts of volatility will be displayed.

$$\sigma_{t+h}^2 = \varphi_0^h\left(b_0 + \sum_{i=1}^{m} \omega_{i0} x_{t-i}^2 + \sum_{j=1}^{H} \omega_{j0} \cdot \varphi_h\left(\sum_{i=1}^{m} \omega_{ij} x_{t-i}^2 + b_j\right)\right).$$

It describes the structure of the model for a single forecasting horizon, where the input (x_{t-i}) can be a matrix of the volatility generated by the GARCH type models and other explanatory variables. The model can be separated into a linear autoregressive component of order and a nonlinear component whose structure depends on the number of hidden nodes which is the hidden layer in ANN.

Figure 1: depicts an example of a feedforward neural network with m features, q hidden nodes and one output.



Source: (Romano, 2019-2020)

3.3. Deep learning:

Deep learning is recently introduced and applied in some of finance literature. Several literatures mainly focus on three types of approaches: Recursive Neural Networks (RNN), Long Short Term Memory (LSTM) and Convolutional neural networks (CNN). Although they are all the extension of normal neural networks, they have different characters when capture data dynamics.

Recursive Neural Networks (RNN) is a class of neural network but deeper than normal neural networks. RNN can use their internal memory to process arbitrary sequence of inputs. The units which can be calculated as a time varying real valued activation and modifiable weight and will form a circle with connect to the networks. RNNs are created by applying the same set of weights recursively over a graph-like structure. Their hidden units can be expressed as:

$$h^t = f(h^{t-1}, x^t; \theta).$$

in the case of RNN, the learned model always has the same input size, because it is specified in terms of transition from one state to another by using the same transition function with the same parameters at each step.

A special extension of RNN called **Long Short-Term Memory (LSTM)** is proposed by (Hochreiter & Schmidhuber, 1997) which replaces the hidden layers with LSTM cells. The cells are composed of various gates including input gate, cell state, forget gate, and output gate that can control the input flow. A sigmoid layer is constructed to describe how much of each component should be let through by generating a series of numbers between zero and one. In addition, a (tanh) layer vector is generated and will be added to the cell state to help the cell state to be updated based on the output gates by point wise multiplication operation (σ). Mathematically, it can be specified as:

The input gate which consists of the input vector (x_i):

$$i_t = \sigma\left(W_{i(h_{t-1}, x_i)} + b_i\right).$$

The cell gate which constructs the entire network, and the information can be added or removed information by the gates vector:

$$c_t = tanh\left(W_{c(h_{t-1}, x_i)} + b_c\right).$$

The forgot gate vector which decides what kind of the information to be allowed:

$$f_t = \sigma\left(W_{f(h_{t-1}, x_i)} + b_c\right).$$

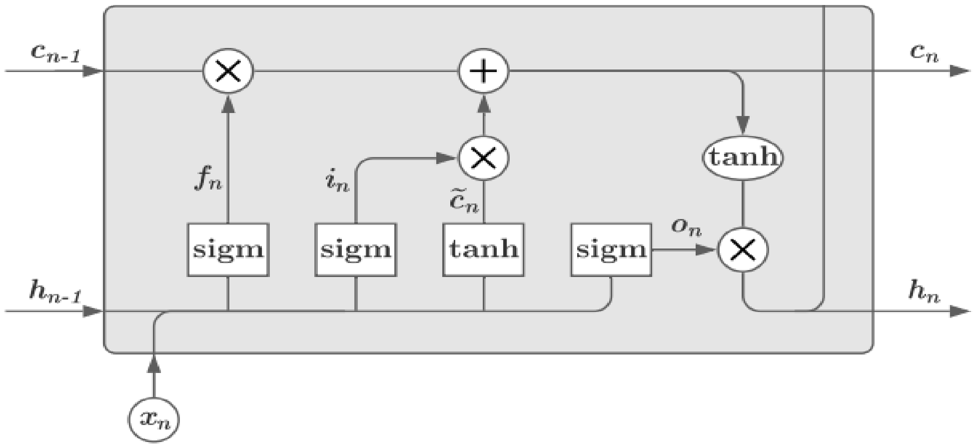
The output gate vector:

$$\mathrm{o_t} = \sigma\left(\mathrm{W_{o(h_{t-1}, x_i)}} + \mathrm{b_o}\right).$$

The output vector:

$$h_t = o_t * \tanh(c_t).$$

Figure 2: Long Short-Term Memory Diagram



Source: (Romano, 2019-2020)

Convolutional neural network (CNN) is another kind of neural network for processing data that has a known topological pattern. The network employs a mathematical operation on processing data called convolution which is a special kind of linear operation instead of general matrix multiplication in at least one of their layers. There is a difference between RNN/ LSTM and CNN. The RNN/LSTM consider long term dependencies which is the long memory facts exists in time series data and uses them for future forecasting while CNN focuses on the given input sequence and does not use any previous history or information during the learning process prediction.

4. Challenges of Predicting Volatility Using Artificial Intelligence Models:

While artificial intelligence holds incredible promise for predicting price movements in financial markets, it is far from a simple or straightforward application. Many challenges are inherently tied to the use of predictive models, along with other related barriers, which can not only limit the use and effectiveness of your models but may also raise regulatory or ethical concerns. In this section, we will discuss the most common challenges encountered when AI models are applied in practice in this field (Aicha, Ben Abdelrahman, & Touiti, 2024).

Data Privacy and Biased Decision-Making: Since fully accurate artificial intelligence will not be available at the outset, this presents various challenges, primarily due to its reliance on historical data when making decisions, which may be inaccurate.

Data Quality and Accountability Requirements for Deploying AI Technology: The predictive power of an algorithm heavily depends on the quality of the data provided as input. Therefore, the limited availability of data with the appropriate quality and quantity may pose an obstacle to the effectiveness of artificial intelligence.

Limited Transparency: AI models can be complex, making it difficult to understand how conclusions are reached. Consequently, this lack of transparency can hinder risk managers' ability to trust and interpret AI outputs.

Technical Expertise: The use of artificial intelligence requires a high level of technical expertise, and organizations may lack the resources or knowledge necessary to implement and maintain AI models.

Security Risks: The storage and processing of large volumes of sensitive data required by artificial intelligence may pose security risks, such as data breaches or cyberattacks targeting the models.

Literature Review:

In recent years, there has been increased interest in the application of artificial intelligence (AI) and machine learning (ML) approaches in financial modeling, specifically in volatility forecasting and risk management. While econometric models (e.g., GARCH and its variants) have traditionally been the most utilized approach for assessing financial time series, they impose linear structures and rely heavily on historical trends to make predictions, limiting their effectiveness in capturing non-linear and/or dynamic patterns in markets. As a result, there is growing interest in exploring AI-based models that can handle large volumes of data, accommodate unstructured inputs and non-linear dependencies, and adapt to rapid changes in the data.

This literature review identifies several relevant empirical studies that directly evaluate the relative performance and complementarity of traditional econometric approaches and AI (ML)-based models. It highlights data sources, methodological innovations, evaluation metrics, and key findings of each study to provide an overview of recent research on the accuracy of volatility forecasting. Collectively, these studies underscore the transformative potential of hybrid structures that combine the economic interpretability of econometric models with the flexibility, adaptability, and accuracy of ML models.

In light of rapid advancements in artificial intelligence (AI) and machine learning (ML), several studies have emerged comparing the effectiveness of these modern approaches to traditional econometric models in financial forecasting.

A notable contribution in this area is the study by (Jadagoudar, 2024) investigated whether artificial intelligence (AI) models outperform traditional econometric approaches, specifically GARCH and ARIMA, in forecasting interest rate movements and corporate bond pricing, particularly during volatile market conditions. The study utilized a comprehensive dataset comprising historical interest rates, corporate bond prices, macroeconomic indicators such as GDP growth and inflation, and unstructured sentiment data from news and social media platforms.

The analysis compared traditional econometric models with AI techniques such as random forests, gradient boosting, and deep learning. Forecasting accuracy was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Theil's U-statistic across both stable and crisis periods, including the 2008 financial crisis and the COVID-19 pandemic.

Findings revealed that AI models, especially deep learning and gradient boosting, significantly outperformed traditional methods by capturing complex, non-linear relationships and incorporating real-time sentiment data. In contrast, GARCH and ARIMA models showed limitations in adapting to sudden market disruptions due to their linear structure and reliance on historical trends.

The study underscores the strength of AI in dynamic financial environments, highlighting its practical value for investors and policymakers. It also proposes hybrid approaches combining AI and traditional models to balance predictive power with interpretability in financial forecasting.

Building on this perspective, (Pérez-Hernández, Arévalo-de-Pablos, & Camacho-Miñano, 2024) proposed a hybrid approach combining artificial neural networks (ANNs) with models such as Support Vector Machines (SVM) and Long Short-Term Memory (LSTM), along with traditional econometric methods: Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA), GARCH(1,1), and GJR-GARCH. The purpose was to enhance volatility forecasting of primary market risk factors: equity risk, exchange rate risk, and credit spread risk, under stable and stressed market conditions.

In the study, daily return data were obtained from Santander Bank shares, IBEX 35 index, Euro/Dollar exchange rates, and the iTraxx Crossover 5-Year credit spread index. In assessing model performance, MAPE (Mean Absolute Percentage Error) estimates were calculated, along with regulatory backtesting metrics such as Value-at-Risk (VaR) and Expected Shortfall (ES), based on the European Central Bank guidelines according to the FRTB (Fundamental Review of the Trading Book).

Research findings disclosed that the hybrid models, in particular those based on SVM and LSTM, outperformed the traditional models during stable periods and exhibited advanced predictive performance, specifically for exchange rate and credit spread risk, while maintaining better scores for equity volatility under EWMA.

The study demonstrates the value of integrating machine learning with econometric models to enhance volatility forecasting and meet regulatory risk management standards.

Similarly, (Liu, Jiang, & Lin, 2022) focused on forecasting the volatility of specific risk for stocks, aiming to improve forecasting accuracy by comparing Long Short-Term Memory (LSTM) neural networks with traditional GARCH models. The study utilized official BARRA financial data, which provided specific risk factors for numerous stocks. A 2-layer LSTM model (hidden size 512) was compared against a baseline GARCH model. The LSTM model used packed specific risk factors of all stocks at each timestamp to capture implicit cross-stock relationships.

The evaluation metrics included Mean Absolute Error (MAE) and Mean Squared Error (MSE). Data preprocessing involved min-max normalization, and the dataset was split into 70% training and 30% testing. The LSTM model was trained for 10 epochs using the Adam optimizer with a specified learning rate and weight decay.

Results showed that the LSTM model significantly outperformed the GARCH baseline, achieving MAE of 0.0730 versus 0.1904 and MSE of 0.0063 versus 0.0380. The innovative approach of packing risk factors of multiple stocks allowed the LSTM model to capture inter-stock dynamics, improving volatility forecasting despite the assumption that specific risks are independent.

This study highlighted the superiority of LSTM neural networks over traditional models, offering a new perspective on modeling cross-stock relationships and providing empirical evidence based on real financial data.

In the same vein, (Yalamati, 2023) investigates the application of artificial intelligence (AI) and machine learning models for forecasting market volatility to enhance financial risk management. The study uses historical market data, including stock prices, trading volumes, and macroeconomic indicators, and applies various machine learning models such as neural networks (including LSTM), support vector machines, and ensemble methods. The models are trained using data splits for training and validation, hyperparameter tuning via grid search, and evaluated through metrics like RMSE, MAE, and accuracy.

Findings show that AI models, particularly LSTM networks, outperform traditional econometric approaches in predicting market volatility. These models demonstrate robustness in adapting to dynamic market conditions and can integrate external information such as macroeconomic variables and sentiment data from news and social media to enhance forecasting accuracy. Despite concerns about interpretability and challenges in real-time data integration, the study confirms the high potential of AI in improving risk management and investment strategies.

Expanding the methodological scope further, (Kumar, Rao, & Dhochak, 2025) presented a hybrid machine learning framework to predict realized volatility within financial markets to improve risk management and decision-making. The authors utilized minute trading data from 2015 to 2022 for three significant markets, namely Infosys (INFY), the Shanghai Stock Exchange Composite Index (SSE), and the National Stock Exchange Index (NIFTY). The greatest innovation of this study is

VMD's integration with multiple deep learning architectures, specifically ANN, LSTM, and GRU, which are further implemented with Q-learning reinforcement algorithms.

The hybrid Q-VMD-ANN-LSTM-GRU model achieved better quantitative and qualitative predictions than the other models and was able to outperform all other models in every market and forecast horizon in the study based on evaluation metrics (e.g., Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE)).

This research is unique due to its methodology, as it combines advanced signal decomposition with state-of-the-art deep learning and reinforcement learning. Moreover, the high-frequency and cross-market data from two significant countries, India and China, provide this research with a breadth of generalization and applicability, particularly for financial institutions and policymakers who are working in dynamic risk spaces.

From a different angle, (Letteri, 2024) developed a volatility-based trading strategy using statistical methods and machine learning to identify patterns in stock prices by recognizing relationships between stocks through volatility. The study used the mean volatility of nine of the largest stocks selected from the NYSE and Nasdaq and applied a k-means++ clustering methodology to group the stocks by similar volatility behavior. The Granger Causality Test was then performed on the clusters to determine whether predictive relationships existed.

The strategy was backtested using metrics such as profit and loss, returns, and performance relative to portfolios based on an optimal strategy, with comparisons made against the Markowitz Efficient Frontier. The results clearly showed that the proposed method outperformed benchmark trading strategy examples, as the model offered a much broader range of potential long and short opportunities based on volatility clustering and Granger Causality.

A notable strength of the study’s trading approach was its novel combination of k-means++ clustering and the Granger Causality Test within a data-driven trading framework based on volatility. This work highlights the predictive value of volatility patterns in financial markets and provides a framework in which both statistical inference and machine learning can support decision-making.

The previous studies can be presented in the following table:

Table 1: Summary of Previous Studies.

Title of the Study	Author(s)	Sample Studied	Study Period	Model Used	Key Findings
Evaluating Artificial Intelligence Superiority Over ARIMA in Forecasting Interest Rates and Corporate Bond Pricing	Ayush Jadagoudar (2024)	Historical interest rates, corporate bond prices, macroeconomic indicators, sentiment data	Historical data	GARCH, ARIMA, Random Forests, Gradient Boosting, Deep Learning	AI models outperformed traditional ones, especially in crises, hybrid approaches recommended for balancing interpretability and accuracy.
A hybrid model integrating artificial neural network with	Francisco Pérez-Hernández, Alvaro	Santander shares, IBEX 35, Euro/Dollar rate, iTraxx	from March 1, 2017 to	ANN, SVM, LSTM, SMA, EWMA,	Hybrid models (especially SVM and LSTM) outperformed

multiple GARCH-type models and EWMA for performing the optimal volatility forecasting of market risk factors	Arévalo-de-Pablos, María-del-Mar Camacho-Miñano (2024)	Crossover Index	April 30, 2021	GARCH(1,1), GJR-GARCH	traditional ones, particularly in forecasting exchange rate and credit spread risk.
Forecasting the Volatility of Specific Risk for Stocks with LSTM	Rui Liua, Yong Jiang ,Jianwu Lina (2021)	BARRA stock-specific risk data	Not specified	LSTM (2-layer), GARCH	LSTM significantly outperformed GARCH by capturing cross-stock relationships, MAE and MSE were substantially lower.
AI and Risk Management: Predicting Market Volatility	Sreedhar Yalamati (2023)	Historical stock prices, volumes, macroeconomic data, sentiment data	Historical data	Neural Networks (incl. LSTM), SVM, Ensemble Models	LSTM outperformed traditional methods, showed high adaptability and robustness in dynamic markets, useful for risk management.
Hybrid ML models for volatility prediction in financial risk management	Satish Kumar, Amar Rao, Monika Dhochak (2025)	Minute-level trading data from INFY, SSE, and NIFTY	from 2015 to 2022.	VMD-ANN-LSTM-GRU	Hybrid model outperformed all others across markets and horizons, combined VMD and reinforcement learning effectively for v
Stock Market Forecasting Using Machine Learning Models Through Volatility-Driven Trading Strategies	Ivan Letteri (2024)	Mean volatility of 9 major NYSE and Nasdaq stocks	Not specified	k-means++ clustering, Granger Causality Test	Strategy outperformed benchmarks, clustering and causality analysis provided more trading opportunities

					based on volatility patterns.

In summary, the studies above provide ample empirical evidence for the use of artificial intelligence models and hybrid models to predict volatility and manage risk in emerging financial markets. Although traditional models also have valid uses dating back years and are important due to their interpretability and regulatory familiarity, machine learning models have demonstrably better predictive performance and are more stable. The combined model is a much more promising approach for researchers, practitioners, and policymakers aiming to navigate increasingly complex financial markets.

Empirical study

Financial markets are rapidly changing, increasing the need for accurate volatility forecasting. Volatility is a key input in many financial models such as derivative pricing and risk estimation. While traditional models like GARCH are widely used, they often fall short in capturing market complexities and sudden shifts. In contrast, artificial intelligence techniques, especially machine learning, offer more flexible tools capable of handling complex market data, making them a promising option for improving volatility prediction accuracy.In this chapter, we will apply artificial intelligence (AI) techniques to volatility forecasting and risk management practices. We will evaluate an AI model using empirical data from the iShares MSCI Emerging Markets ETF (EEM) and compare its results with the econometric techniques we discussed in earlier chapters. Our purpose here is to assess the role of effective volatility forecasting in emerging markets and to examine the extent to which these models are suitable for supporting risk management decisions.

Building on the foundations laid in Chapters One and Two, this chapter continues to explore volatility forecasting and risk management using the same dataset, estimation periods, and forecasting horizons. The analysis is performed using Python 3.13 and OxMetrics, allowing for a comprehensive and robust comparison of different modeling approaches.

1. Overview of the data:

In this chapter, we build on the foundation laid in Chapters One and Two by analyzing the daily closing prices of the iShares MSCI Emerging Markets ETF (symbol: EEM). The dataset is divided into 5,225 observations for training and 127 observations for testing to ensure robust model evaluation. All statistical analyses were conducted using Python version 3.13 and OxMetrics version 7.2.

The forecasting period extends from March 25, 2024 to September 24, 2024, covering a range of time horizons to assess the model's predictive accuracy over both short- and medium-term intervals.

The forecast horizons are defined as follows:

Short horizon:

One-day forecast: from March 25, 2024, to March 26, 2024.

One-week forecast: from March 25, 2024, to April 1, 2024.

Medium horizon:

One-month forecast: from March 25, 2024, to April 25, 2024.

Three-month forecast: from March 25, 2024, to June 25, 2024.

Considered as long-term horizon:

Six-month forecast: from March 25, 2024, to September 24, 2024.

These time frames were selected to provide a comprehensive evaluation of the model's adaptability and performance under varying market conditions.

2. Methodology:

This Chapters seeks to compare the performance of traditional econometric models and artificial intelligence-based models in forecasting financial market volatility. The analysis is structured into three main stages, noting that model estimation has already been carried out in previous chapters. This chapter is dedicated solely to the forecasting process.

the first Step, the previously estimated ARMA(2,1)-GARCH(1,2) model is employed to generate volatility forecasts. In the second Step, a Long Short-Term Memory (LSTM) model is used to produce forecasts using the same time series data as the ARMA(2,1)-GARCH(1,2) model. The LSTM model is fed historical values of the series and outputs predicted volatility over the same forecast horizon, ensuring a consistent basis for comparison. In the final Step, the forecasting performance of both models is evaluated using standard accuracy metrics, including Mean Squared Error (MSE) and Mean Absolute Error (MAE), with the aim of assessing each model's effectiveness in capturing volatility dynamics and determining which provides superior forecasting accuracy.

2.1. Long Short-Term Memory (LSTM):

LSTM is one of the most well-known neural network models used for processing sequential data, such as time series prediction. We have previously explained its internal mechanisms in detail, including the different gates and how the internal state is updated.

In this context, we will focus on the use of LSTM due to its strong ability to capture short and long-term dependencies.

Advantages of LSTM:

Captures Temporal Dependencies: LSTMs can learn complex temporal patterns and long-range dependencies in financial data, which are often missed by simpler models.

Captures Non-linearity: Given the inherently non-linear nature of financial markets, LSTMs are well-suited to model and learn these complex, non-linear relationships effectively.

Robust to Noise (to some extent): While financial data is noisy, the gating mechanism can help LSTMs to selectively focus on relevant information.

2.2. Evaluation Metrics

Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are two common metrics used to measure the accuracy of a predictive model. They quantify the difference between predicted values and actual values.

2.2.1. Mean Absolute Error (MAE)

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average of the absolute differences between the predicted and actual values.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Where:

- $\boldsymbol{n}$: is the number of observations.
- $\boldsymbol{y_i}$: is the actual value for the i-th observation.
- $\boldsymbol{\hat{y}_i}$: is the predicted value for the i-th observation.

Interpretation: A lower MAE indicates a better fit of the model to the data.

2.2.2. Root Mean Squared Error (RMSE):

RMSE is the square root of the average of the squared differences between predicted and actual values. It represents the standard deviation of the residuals (prediction errors).

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where:

- $\boldsymbol{n}$: is the number of observations.
- $\boldsymbol{y_i}$: is the actual value for the i-th observation.
- $\boldsymbol{\hat{y}_i}$: is the predicted value for the i-th observation.

These metrics provide an aggregate measure of forecast accuracy, with lower values indicating better performance. The reported MAE and RMSE values are the means of the absolute and squared errors, respectively, over the forecast evaluation period.

3. Results and discussion:

3.1 Step One: Implementing Out-of-Sample Forecasting Using Traditional Models (ARMA(2-1)-GARCH(1-2)).

In this section, we will use the ARMA(2-1)-GARCH(1-2) model to predict volatility, as it is specifically designed to model time-varying volatility in financial data. ARMA(2-1)-GARCH(1-2) effectively captures volatility , making it suitable for accurate forecasting.

This section presents the empirical results regarding the forecasting performance of the proposed model across various time horizons: 1 day, 1 week (5 days), 22 days (approximately one month), 66 days (approximately one quarter), and 127 days (approximately half a year). The analysis focuses on evaluating the accuracy of the conditional mean and conditional variance forecasts across these five distinct forecast horizons.

3.1.1 One-Day Ahead Forecasts (N=1)

- The forecasted mean is -0.0002226.
- The forecasted variance is 0.00007823.

The evaluation metrics for the mean and Variance forecast are:

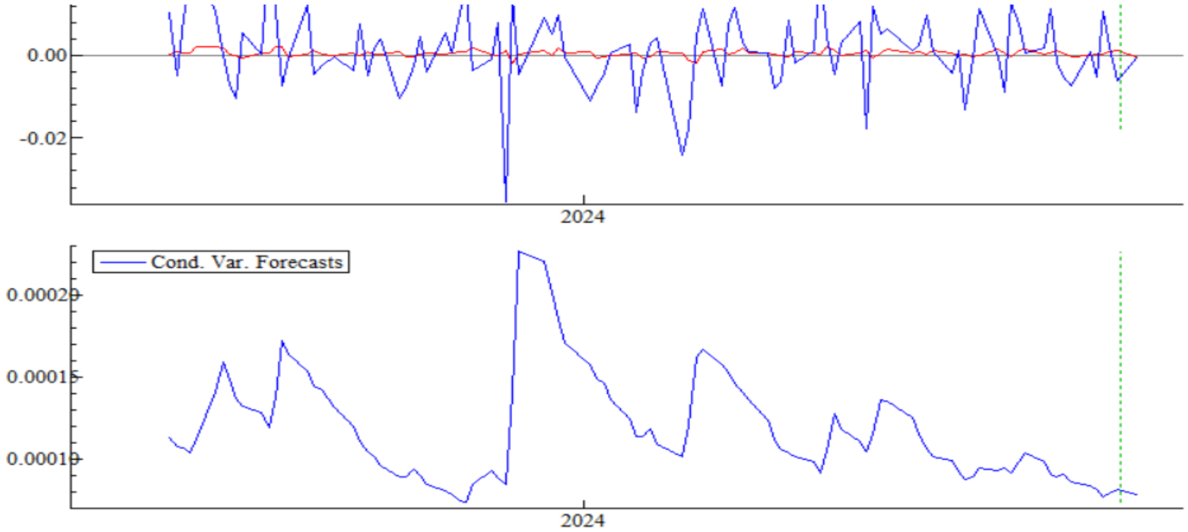
Table 1: The evaluation metrics for the mean and Variance forecast (N=1).

Forecast Evaluation Measures	Mean	Variance
Mean Absolute Error (MAE)	**0.0003384**	**0.00007823**
Root Mean Squared Error (RMSE)	**0.0003384**	**0.00007823**

Source: Outputs of the Oxmetrics 7.2

The low magnitude of both MAE and RMSE suggests that the model is highly precise for short-term predictions. The equality of MAE and RMSE suggests a single forecast error observation, which is expected for an N=1 forecast evaluation if it's based on a single out-of-sample point. These metrics provide a baseline for error magnitude at the shortest forecast horizon.

Figure 1: Conditional Mean Forecasts with Residuals, and Conditional Variance Forecasts N=1



Source: Outputs of the Oxmetrics 7.2

Conditional Mean Forecasts and Residuals: The top panel displays the conditional mean forecasts (red line) hovering close to zero, with the residuals (blue line) fluctuating around this mean. These residuals exhibit periods of varying volatility. The green dashed line indicates the single-step ahead forecast point.

Conditional Variance Forecasts: The bottom panel shows the conditional variance forecasts (blue line), which display some fluctuation, reflecting changes in volatility over the observed period.

3.1.2 One-Week Ahead Forecasts (N=5)

For the 1-week (5-step ahead) horizon, the conditional mean forecasts show some dynamics over the 5 steps, starting at -0.0002226 and reaching 0.0005411 by the 5th step. The conditional variance forecasts show a slight increase from 7.823e-005 at step 1 to 8.928e-005 at step 5, indicating increasing uncertainty over the week.

The aggregate evaluation metrics for the and Variance forecasts over this horizon are:

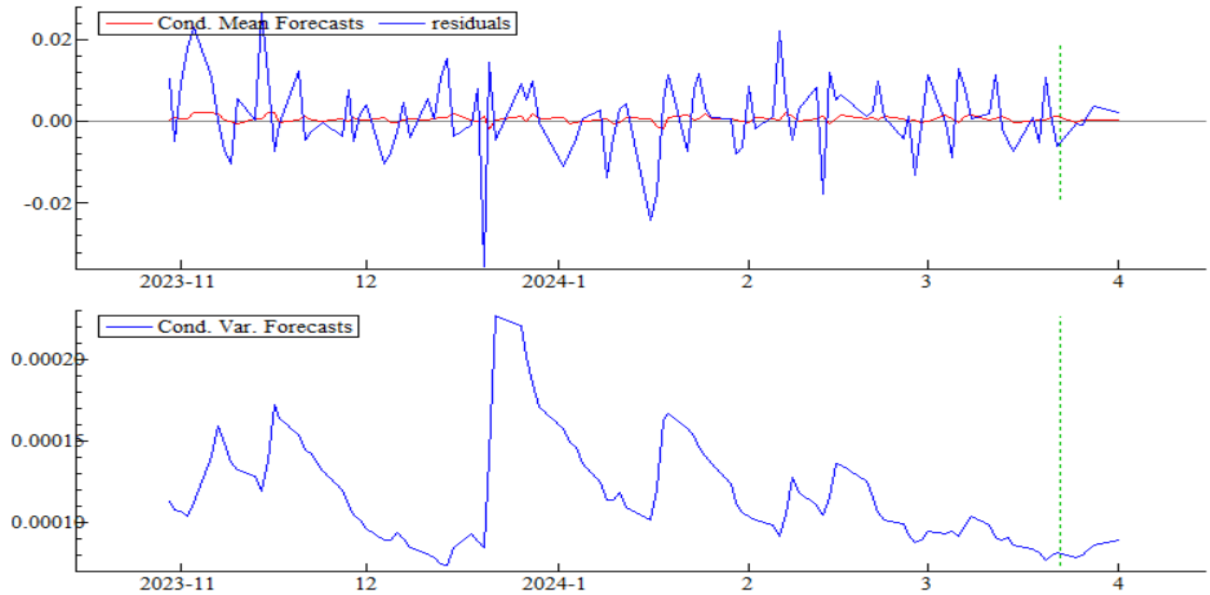
Table 2: The evaluation metrics for the mean and Variance forecast (N=5).

Forecast Evaluation Measures	Mean	Variance
Mean Absolute Error (MAE)	0.001528	0.0000794
Root Mean Squared Error (RMSE)	0.001808	0.00007949

Source: Outputs of the Oxmetrics 7.2

slight decrease in MAE and RMSE values is observed when forecasting variance compared to the one-day horizon, which may indicate that the model captures short-term variance dynamics over five steps slightly better overall than for a single day.

Figure 2: Conditional Mean Forecasts with Residuals, and Conditional Variance Forecasts N=5



Source: Outputs of the Oxmetrics 7.2

Conditional Mean Forecasts and Residuals: Similar to the one-day forecast graph, the conditional mean forecast (red line) remains close to zero, while residuals (blue line) fluctuate around it.

Conditional Variance Forecasts: The conditional variance forecast (blue line) continues to show variability. The green dashed line indicates the forecast period.

3.1.3 One-Month Ahead Forecasts (N=22):

The multi-step mean forecasts tend to stabilize around a small positive value (approximately 0.00054) after the initial few steps.

The conditional variance forecasts exhibit a persistent upward trend across the 22 steps, starting from 0.00007823 and increasing to 0.0001317 by the 22nd step. This illustrates the accumulation of uncertainty as the forecast horizon extends.

The evaluation metrics for the mean and Variance forecasts are:

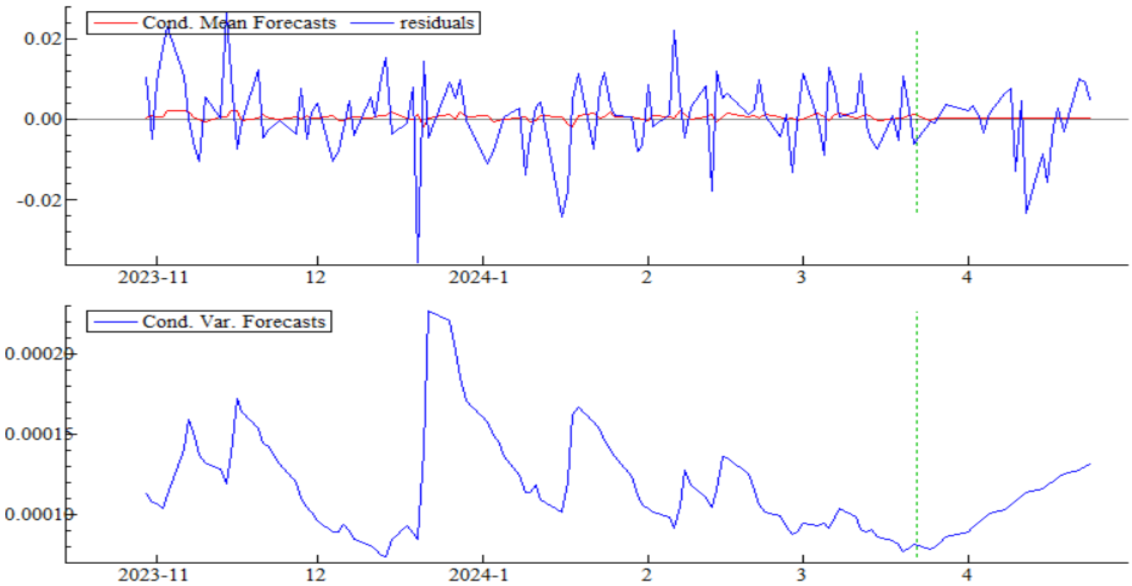
Table 3: The evaluation metrics for the mean and Variance forecast (N=22).

Forecast Evaluation Measures	Mean	Variance
Mean Absolute Error (MAE)	0.005754	0.0000986
Root Mean Squared Error (RMSE)	0.008093	0.000126

Source: Outputs of the Oxmetrics 7.2

For the one-month horizon, while the mean forecast stabilizes at a low level, the model predicts a clear increase in variance, suggesting growing uncertainty about future values. The MAE and RMSE values quantify the average error magnitude for these forecasts, with RMSE being higher than MAE, indicating some larger errors are present.

Figure 3: Conditional Mean Forecasts with Residuals, and Conditional Variance Forecasts N=22



Source: Outputs of the Oxmetrics 7.2

Conditional Mean Forecasts and Residuals: The top panel, with a visible timeline from November 2023 to early 2024, shows the conditional mean forecast (red line) steady near zero. The residuals (blue line) continue to fluctuate.

Conditional Variance Forecasts: The bottom panel clearly depicts the conditional variance forecast (blue line) trending upwards during the forecast period (to the right of the green dashed line), visually confirming the statement of increasing uncertainty over the month-long horizon.

3.1.4 Three-Month Ahead Forecasts (N=66)

For the 3-month (66-step ahead) horizon:

The conditional mean forecasts remain stable around 0005427 for the majority of the forecast steps beyond the initial periods.

The conditional variance forecasts continue their clear upward trajectory, rising from 0.00007823 at step 1 to 0.0001914 at step 66. This signifies a substantial increase in predicted uncertainty at this longer horizon.

The evaluation metrics for the mean and Variance forecasts are:

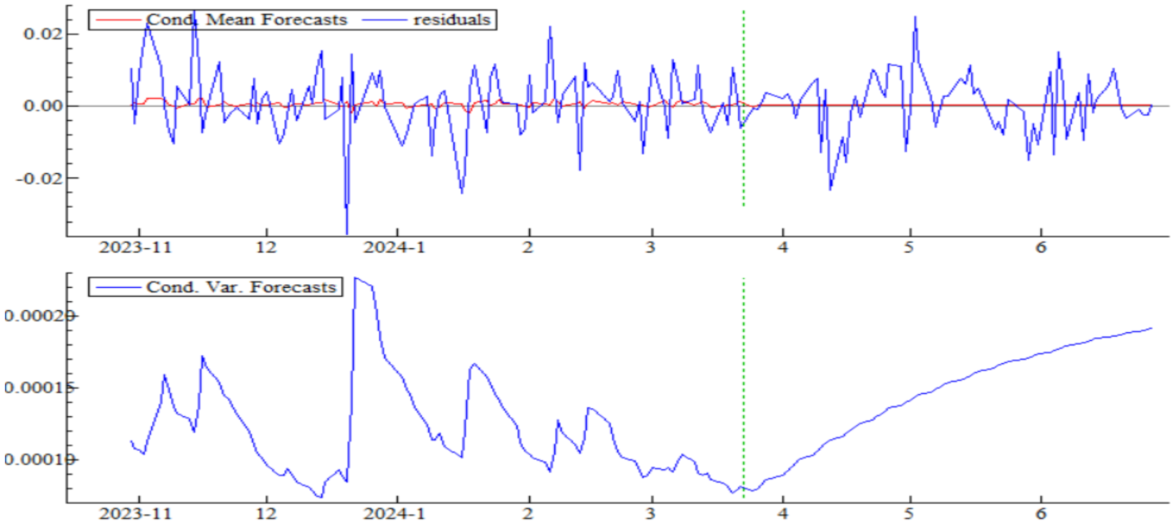
Table 4: The evaluation metrics for the mean and Variance forecast (N=66).

Forecast Evaluation Measures	Mean	Variance
Mean Absolute Error (MAE)	0.006225	0.0001172
Root Mean Squared Error (RMSE)	0.008163	0.0001405

Source: Outputs of the Oxmetrics 7.2

At the three-month horizon, the mean forecast remains stable, similar to the one-month outlook, but at a slightly different approximated value. However, the increase in conditional variance indicating a greater degree of uncertainty in the forecasts. This is also reflected in the MAE and RMSE values for variance, which are higher than those for the one-month horizon (0.0001172 vs 9.86e-005 for MAE, and 0.0001405 vs 0.000126 for RMSE). Similarly, the error metrics for the mean forecast are also slightly higher than for the one-month horizon, indicating reduced accuracy.

Figure 4: Conditional Mean Forecasts with Residuals, and Conditional Variance Forecasts N=66



Source: Outputs of the Oxmetrics 7.2

Conditional Mean Forecasts and Residuals: The mean forecast (red line) continues its stable pattern near zero.

Conditional Variance Forecasts: The upward trend in the conditional variance forecast (blue line) beyond the green dashed line is more pronounced and extended, consistent with the described substantial increase in uncertainty.

3.1.5 Extending to the 6-month (127-step ahead) horizon:

Similar to the 3-month horizon, the conditional mean forecasts stabilize around 0.0005427 for most of the forecast steps. The conditional variance forecasts continue to rise steadily, reaching 0.0002198 by the 127nd step. This highlights the significant uncertainty associated with forecasts six months into the future.

The evaluation metrics for the mean and Variance forecasts are:

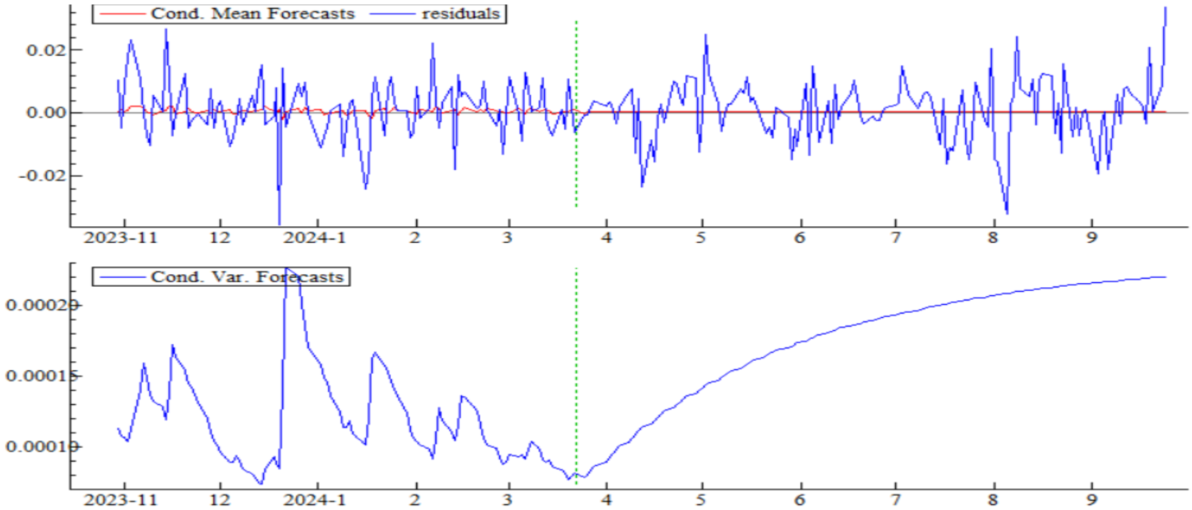
Table 5: The evaluation metrics for the mean and Variance forecast (N=127).

Forecast Evaluation Measures	Mean	Variance
Mean Absolute Error (MAE)	**0.007405**	**0.0001464**
Root Mean Squared Error (RMSE)	**0.009808**	**0.0001873**

Source: Outputs of the Oxmetrics 7.2

For the six-month horizon, the mean forecast shows consistency in its stable, low-level prediction. However, the forecasted conditional variance reaches its highest point among the three analyzed periods, emphasizing a considerable build-up of uncertainty. This is quantitatively supported by the MAE and RMSE values for variance (0.0001464 and 0.0001873 respectively), which are the largest observed across the one-month, three-month, and six-month horizons. The error metrics for the mean forecast also continue to increase, further indicating that forecast accuracy diminishes substantially at this extended range.

Figure 5: Conditional Mean Forecasts with Residuals, and Conditional Variance Forecasts N=127



Source: Outputs of the Oxmetrics 7.2

Conditional Mean Forecasts and Residuals: The mean forecast (red line) maintains its stability close to zero.

Conditional Variance Forecasts: The upward climb of the conditional variance forecast (blue line) is very clear and extends significantly further into the future, visually emphasizing the substantial increase in forecast uncertainty over this long horizon.

Summary of Forecast Accuracy Metrics Across Different Time Horizons: RMSE and MAE for Mean and Variance Forecasts.

Table 6: Summary of Forecast Accuracy Metrics Across Different Time Horizons: RMSE and MAE for Mean and Variance Forecasts.

Forecast Horizon	Number of Forecasts	MAE		RMSE	
		Mean	Variance	Mean	Variance
1 Day	1	0.0003384	0.00007823	0.0003384	0.00007823
1 Week	5	0.001528	0.0000794	0.001808	0.00007949
1 Month	22	0.005754	0.0000986	0.008093	0.000126
3 Months	66	0.006225	0.0001172	0.008163	0.0001405
6 Months	127	0.007405	0.0001464	0.009808	0.0001873

Source: Outputs of the Oxmetrics 7.2

In summary, the forecasting demonstrates that while the mean of the series is predicted to remain relatively stable at a low level, the uncertainty surrounding these forecasts, as captured by the conditional variance, grows substantially with the length of the forecast horizon. This is a critical consideration for any decision-making based on these forecasts, particularly for longer-term outlooks. The increasing error metrics (MAE and RMSE) with the horizon further underscore the diminishing reliability of point forecasts further into the future. These findings are consistent with typical behaviors observed in financial markets, where long-range forecasting is inherently challenging due to accumulating volatility and unforeseen shocks.

3.2. Step Two: Implementing Out-of-Sample Forecasting Using artificial intelligence models (LSTM)

This section presents the results obtained from employing a Long Short-Term Memory (LSTM) model to forecast residuals. The analysis is structured into an evaluation of the model's quality and predictive validity, followed by a detailed interpretation of its forecasting performance, supported by graphical outputs.

3.2.1 Model Overview and Structure:

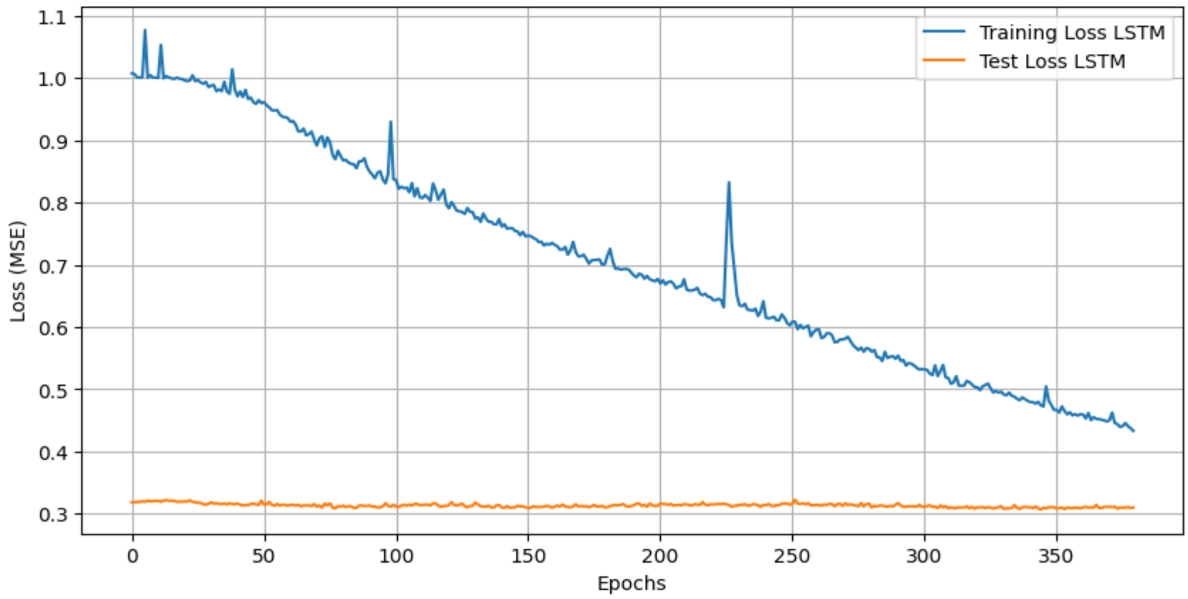
The Long Short-Term Memory (LSTM) model implemented in this study features a two-layer architecture with 256 hidden units and dropout regularization (p = 0.2). It was trained on residual series data, which isolates the unpredictable component after filtering out the trend and seasonality. This approach aligns well with econometric best practices in time series modeling, where modeling residuals can improve forecast precision by focusing on the stochastic components.

The input data structure consisted of a training set with shape (5225, 40) and a test set of shape (127, 40). This input configuration signifies the use of 40-lag windows to predict the next data point, enabling the model to capture temporal dependencies.

3.2.2 Evaluation of LSTM Model Quality and Predictive Validity:

The model underwent training for 380 epochs. Observation of the "Figure 6" graph reveals a generally decreasing training loss over the epochs. The training loss decreased from 1.000758 to 0.433218, while the test loss decreased to 0.310023, reflecting an effective learning process with no signs of overfitting. The gap between training and test losses remained narrow throughout, indicating the model generalized well to unseen data.

Figure 6: LSTM Training and Test Loss.

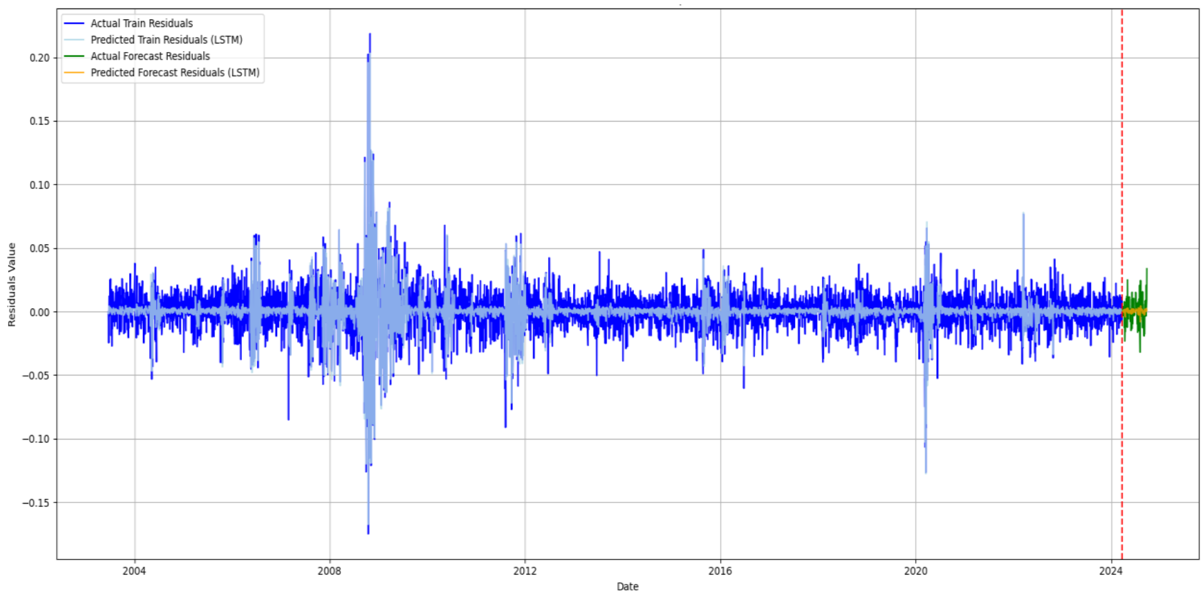


Source: Outputs of the Python 3.13

3.2.3 Detailed Analysis of LSTM Forecasting Performance on Residuals.

(Figure 7) illustrates the comparison between actual and predicted residuals generated by the LSTM model, covering both the training and forecasting periods. The red vertical dashed line demarcates the boundary between these two phases.

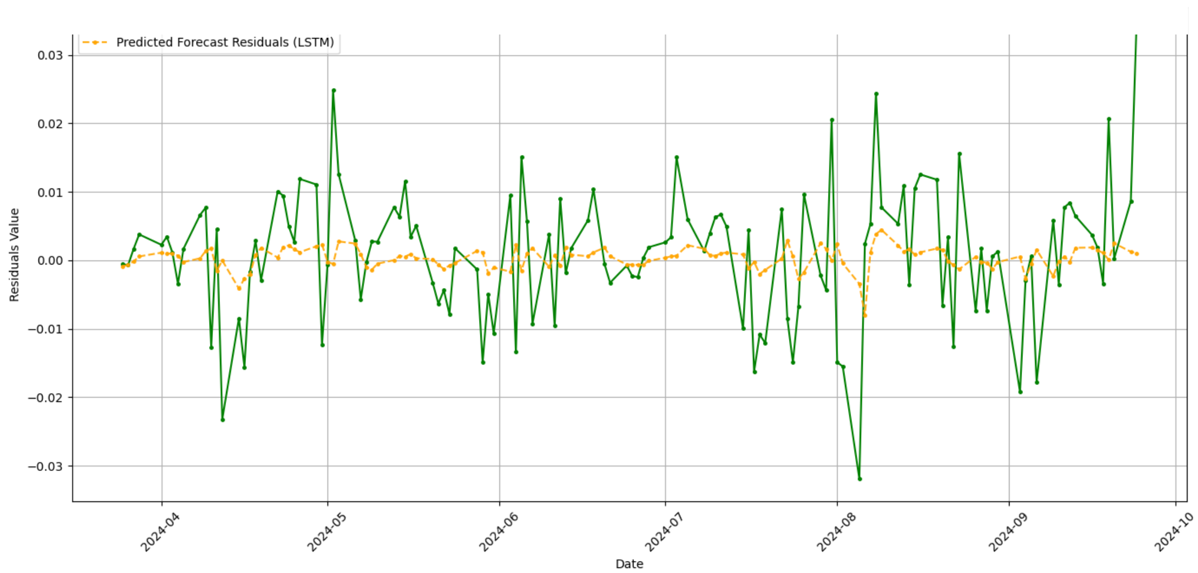
Figure 7: LSTM Predictions vs Actual Residuals



Source: Outputs of the Python 3.13

During the training period (before the red vertical line), the LSTM model demonstrates a strong ability to learn and replicate patterns from the residual series. The predicted residuals (light blue line) closely follow the actual residuals (dark blue line). Although some deviations are observed during periods of high volatility (particularly around the 2008 and 2020 financial crisis), the model generally aligns well with the actual data, indicating that it successfully captured the underlying stochastic patterns.

Figure 8: Focused LSTM Forecast vs Actual Residuals



Source: Outputs of the Python 3.13

In the forecasting period (Figure 8), the graph clearly shows that the LSTM's predictions for residuals (the orange dashed line) attempt to track the general direction of the actual residuals (the green solid line), often moving in the same direction as the actual fluctuations. However, the most prominent feature is that the LSTM predictions are significantly smoother and lack the sharpness of the fluctuations seen in the actual residuals. The model consistently tends to underestimate the magnitude of high peaks and deep troughs that occur in reality (as is evident, for example, in the large drop near early August or the rise near the end of September 2024, where the LSTM's response is much less pronounced). This means that while the model captures some dynamics, it fails to predict the full magnitude of large fluctuations or "shocks" in the errors.

Table 7: Table 7Forecast Accuracy Metrics Across Different Time Horizons: RMSE and MAE for Mean and Variance Forecasts.

Forecast Horizon	Number of Forecasts	MAE		RMSE	
		Mean	Variance	Mean	Variance
1 Day	1	0.00030814	0.00000044	0.00030814	0.00000044
1 Week	5	0.00131678	0.00000426	0.00174316	0.00000664
1 Month	22	0.00527381	0.00006256	0.00761698	0.00013456
3 Months	66	0.00607293	0.00006538	0.00815626	0.00012772
6 Months	127	0.00731133	0.00009536	0.00968228	0.00019504

Source: Outputs of the Python 3.13

The table shows how forecasting performance changes across different time horizons through the analysis of (RMSE) and (MAE). The data indicates that both RMSE and MAE values grow in mean and variance across all time horizons from 1 day to 6 months. The results show that forecasting accuracy deteriorates while forecasting error dispersion becomes larger thus indicating reduced precision.

The analysis supports the conclusion that longer time horizons lead to decreased forecast accuracy precision together with increased uncertainty about predicted results.

3.3 Step three: A Comparative Analysis of ARMA-GARCH and LSTM Models.

This section presents a comparative analysis between the traditional econometric approach (ARMA(2-1)-GARCH(1-2)) and the machine learning-based approach (LSTM) applied to the iShares MSCI Emerging Markets ETF (EEM). Both models were applied to identical datasets and evaluated using consistent out-of-sample performance metrics across various time horizons. Through this comparative analysis, we seek to identify the model that provides higher accuracy and reliability in forecasts for different time periods.

Our evaluation centers around three primary factors:

- **Forecast Accuracy:** Quantified using MAE and RMSE for both conditional mean and conditional variance.
- **Model Robustness Across Horizons:** Assessing performance consistency from short-term (1 day) to long-term (6 months) horizons.
- **Forecast Responsiveness to Shocks:** Evaluating how well each model captures sudden market changes or volatility spikes.

3.3.1 Comparative Analysis of Forecast Accuracy:

To assess the comparative forecast accuracy of the LSTM and ARMA(2,1)-GARCH(1,2) models, we classify the magnitude of difference in error metrics (MAE and RMSE) into four categories based on the percentage difference between the models' values:

- **Negligible:** Less than 0.5%.
- **Slight:** From 0.5% to less than 5%.
- **Moderate:** From 5% to less than 20%.
- **Significant:** 20% or more.

The table below summarizes the RMSE and MAE values for both models across the selected forecast horizons, along with the classified magnitude of difference:

Table 8: Summarizes the RMSE and MAE values for both models across the selected forecast horizons, along with the classified magnitude of difference.

Forecast Horizon	Metric	Forecast Type	ARMA(2-1)-GARCH(1-2) Value	LSTM Value	Lower Error (Better)	Relative Diff	Magnitude of Difference
1 Day	MAE	Mean	0.0003384	0.00030814	LSTM	8.94%	Moderate
	RMSE	Mean	0.0003384	0.00030814	LSTM	8.94%	Moderate
	MAE	Variance	0.00007823	0.00000044	LSTM	99.44%	Significant
	RMSE	Variance	0.00007823	0.00000044	LSTM	99.44%	Significant
1 Week	MAE	Mean	0.001528	0.00131678	LSTM	13.82%	Moderate
	RMSE	Mean	0.001808	0.00174316	LSTM	3.59%	Slight
	MAE	Variance	0.0000794	0.00000426	LSTM	94.63%	Significant
	RMSE	Variance	0.00007949	0.00000664	LSTM	91.65%	Significant
1 Month	MAE	Mean	0.005754	0.00527381	LSTM	8.35%	Moderate
	RMSE	Mean	0.008093	0.00761698	LSTM	5.88%	Moderate
	MAE	Variance	0.0000986	0.00006256	LSTM	36.55%	Significant

	RMSE	Variance	0.000126	0.00013456	ARMA-GARCH	6.36%	Moderate
3 Months	MAE	Mean	0.006225	0.00607293	LSTM	2.44%	Slight
	RMSE	Mean	0.008163	0.00815626	LSTM	0.08%	Negligible
	MAE	Variance	0.0001172	0.00006538	LSTM	44.22%	Significant
	RMSE	Variance	0.0001405	0.00012772	LSTM	9.10%	Moderate
6 Months	MAE	Mean	0.007405	0.00731133	LSTM	1.26%	Slight
	RMSE	Mean	0.009808	0.00968228	LSTM	1.28%	Slight
	MAE	Variance	0.0001464	0.00009536	LSTM	34.86%	Significant
	RMSE	Variance	0.0001873	0.00019504	ARMA-GARCH	3.97%	Slight

Source: Outputs of Oxmetrics 7.2 and Python 3.13

Short-Term Forecasts (1 Day to 1 Week): The LSTM model demonstrates slightly superior performance in both mean and variance forecasting, with significantly lower variance RMSEs.

Medium-Term Forecasts (1 to 3 Months): The models converge in performance. While LSTM continues to show slightly better MAEs for the mean, ARMA(2-1)-GARCH(1-2) occasionally performs better in variance prediction.

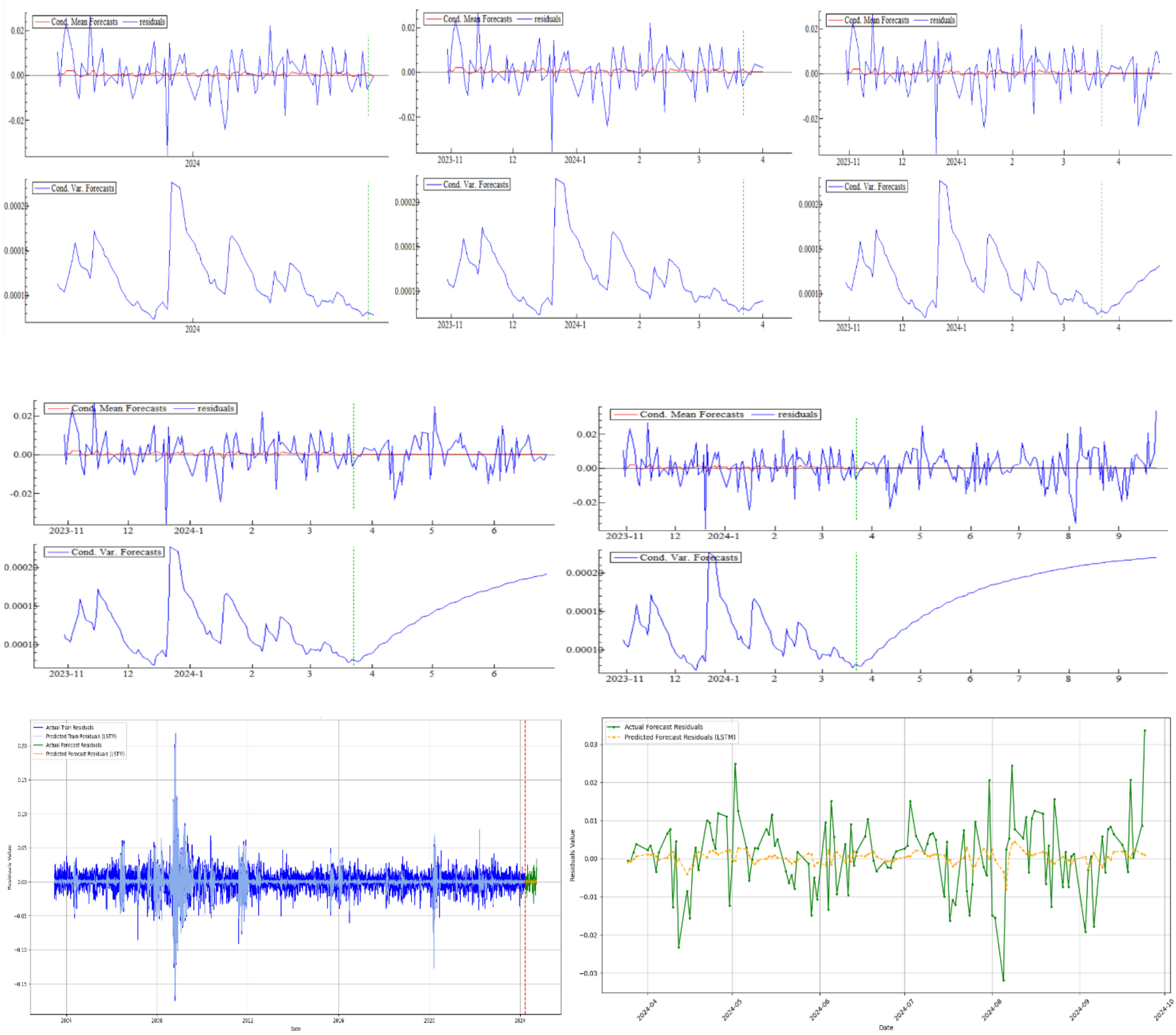
Long-Term Forecast (6 Months): Both models demonstrate declining accuracy, with the LSTM model continuing to show slightly better mean forecast metrics. Its variance prediction is only slightly worse than that of the ARMA(2-1)-GARCH(1-2) model, suggesting it is less sensitive to increasing uncertainty.

3.3.2 Comparative Analysis of Graphical Representation Methods:

The visual outputs reinforce the numerical findings. For the ARMA(2-1)-GARCH(1-2) model, the variance plots visibly show a gradual increase in forecast uncertainty. This is consistent with financial theory and reinforces the credibility of its variance predictions. Conversely, the LSTM model provides smoother forecasts with less visible volatility escalation. Although this implies stability, it also reflects an underestimation of market shocks, especially during high-volatility periods like the 2008 or 2020 financial crises.

The LSTM model's structural learning is grounded in capturing historical temporal patterns. However, it is often criticized for under-reacting to rare but impactful events, due to its reliance on minimizing average error during training. In contrast, ARMA(2-1)-GARCH(1-2) models are statistically tailored to volatility clustering, and therefore, their forecasts respond more dynamically to residual shocks, albeit sometimes at the cost of mean forecast precision.

Figure 9: Comparative graphical analysis of forecast outputs from ARMA-(2-1)-GARCH(1-2) and LSTM models



Source: Outputs of Oxmetrics 7.2

Chapter conclusion:

Based on the provided empirical evidence, the LSTM model generally demonstrates superior quantitative forecast accuracy for both mean and variance, particularly when assessed by MAE. It consistently yields lower MAE and RMSE for mean forecasts across all horizons. For variance forecasts, LSTM achieves significantly lower MAE across all horizons, aligning with findings reported in the previously mentioned literature..

However, this superiority comes with a caveat. The ARMA(2-1)-GARCH(1-2) model's strength lies in its explicit and progressively increasing conditional variance forecasts, which transparently reflect growing uncertainty, a stylized fact of financial time series. The slightly better performance of ARMA(2-1)-GARCH(1-2) in variance RMSE at the 1-month and 6-month horizons might indicate it handles some large errors better at these specific points.

The LSTM model’s tendency to smooth volatile residual movements implies that its lower error metrics for variance might be achieved partly by not fully capturing the amplitude of extreme shocks. While it is more accurate on average, its depiction of risk, especially tail risk, might be less pronounced than that of ARMA(2-1)-GARCH(1-2).

Therefore, if the primary criterion is minimizing average forecast error statistics, the LSTM model appears to be the superior choice based on this study. However, for applications where a more conservative and explicit representation of escalating uncertainty and the potential magnitude of shocks is paramount, the ARMA(2-1)-GARCH(1-2) model's characteristics remain highly valuable despite its slightly higher average error metrics in most cases. The choice of model could thus also depend on the specific application and the user's risk tolerance and objectives. Future research could explore hybrid models that combine the strengths of both approach.

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General Conclusion

The aim of this study is to analyze and compare the performances of traditional (econometric) and Artificial Intelligence (AI)-based volatility forecasting models in emerging financial markets, in the context of risk management. The comparative value of traditional versus AI-based models is important, given the volatility of emerging markets and their sensitivity to the global economy, making effective volatility management essential for investors and policymakers.

To achieve the research objectives, historical daily price data of the iShares MSCI Emerging Markets ETF (EEM) were analyzed, adopting a descriptive, analytical, and econometric methodology within a positivist philosophical framework. The study was organized into successive chapters, beginning with a introductory chapter that established the conceptual framework for emerging markets, Exchange-Traded Funds (ETFs), the MSCI Emerging Markets Index, and the associated EEM fund. This was followed by the first chapter, which addressed volatility forecasting in emerging markets with an applied analysis using traditional econometric tools (ARMA-GARCH) on the fund's data. The second chapter focused on risk management in emerging financial markets, with an applied evaluation of risk metrics such as Value at Risk (VaR) using traditional models (Parametric VaR, ARMA-GJR-GARCH). Finally, the third chapter presented a comparative analysis between traditional and AI-based models (LSTM) in forecasting and risk management, using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics.

The main findings of the study revealed several important aspects. Regarding traditional volatility modeling (Chapter One), the analysis of EEM closing prices showed non-stationarity, necessitating log transformation and first differencing (log returns) to achieve stationarity. No significant long-memory was detected in the stationary return series. However, statistically significant ARCH effects and serial correlation were observed. An ARMA(2,1) model was selected for the mean equation, but its residuals still exhibited ARCH effects, thus requiring GARCH models. The ARMA(2,1)-GARCH(1,2) model with a Skewed Student’s t-distribution was deemed most suitable for modeling the volatility of EEM returns in-sample. Out-of-sample forecasts from this model showed increasing uncertainty (variance) and error metrics (MAE, RMSE) as the forecast horizon extended from one day to six months.

Concerning traditional risk management (Chapter Two), the simple parametric VaR model proved inadequate, failing Kupiec LR tests for all confidence levels. The ARMA(2,1)-GARCH(1,2) model used for VaR estimation passed Kupiec tests but showed weaknesses in Dynamic Quantile (DQ) tests for long positions at stricter confidence levels, indicating clustering of exceptions. In contrast, the ARMA(2,1)-GJR-GARCH(2,1) model emerged as the most effective for VaR estimation, successfully passing both Kupiec LR and DQ tests and capturing asymmetries in returns, with some minor ARCH effects remaining in residuals, which were considered acceptable for practical purposes. This illustrated a key trade-off: the ARMA-GARCH model, identified in Chapter One as more suitable for volatility forecasting, proved less robust for risk management (due to the aforementioned DQ test failure), while the ARMA-GJR-GARCH model, though demonstrating superior performance for risk management by satisfying both Kupiec and DQ tests, exhibited poorer performance for volatility forecasting tasks.

The comparative analysis between the traditional approach and AI (Chapter Three) showed that the Long Short-Term Memory (LSTM) model generally demonstrated superior quantitative forecast accuracy (lower MAE and RMSE for the mean, lower MAE for variance) compared to the ARMA(2,1)-GARCH(1,2) model across various time horizons. However, the ARMA(2,1)-GARCH(1,2) model provided a clearer representation of escalating uncertainty with longer horizons and performed slightly better in variance RMSE at the 1-month and 6-month horizons specifically.

The LSTM model tended to smooth volatile movements, which might lead to an underestimation of rare market shocks, thereby providing a less pronounced depiction of tail risk despite better average error metrics.

Based on these results, the study's hypotheses were verified. The data showed that EEM markets are characterized by higher volatility (as evidenced by the need to employ a higher-order GARCH model such as GARCH(1,2), which captures more complex and persistent volatility dynamics compared to the commonly used GARCH(1,1) in previous literature) (Sub-hypothesis 1) and exhibit volatility clustering (Sub-hypothesis 2). Models accounting for heteroscedasticity outperformed the simple parametric VaR (Sub-hypothesis 3). Regarding the main hypothesis and (Sub-hypothesis 4) concerning the superiority of AI models, the results generally supported this in terms of average error metrics, but with the caveat that traditional GARCH models better reflected escalating uncertainty and responsiveness to shocks.

This study offers significant theoretical and practical contributions. Theoretically, it provides recent empirical evidence on the performance of different models in the context of volatile emerging markets. Practically, the findings suggest that investors and risk managers in emerging markets should balance the average forecast accuracy that AI models may offer with the deep understanding of risk dynamics, including tail risk and escalating uncertainty, which traditional models (like the GARCH family) excel at highlighting. Thus, the choice of the optimal model depends on the specific objective of the analysis and the desired practical application, whether it is minimizing average error or conservatively assessing potential risks.

Based on the foregoing, the study recommends the following:

For investors seeking to minimize average forecast error, AI models (like LSTM) can offer superior performance.

For risk management purposes requiring a conservative and precise understanding of escalating uncertainty and major shock risks, traditional GARCH-family models (especially GJR-GARCH for VaR estimation) remain indispensable tools.

Confirmation that the EEM ETF indeed reflects characteristics of volatility, and leverage effects that necessitate sophisticated modeling.

Finally, this study opens avenues for future research, including:

Innovate by developing hybrid models that integrate the distinct advantages of both econometric analysis and AI-driven techniques.

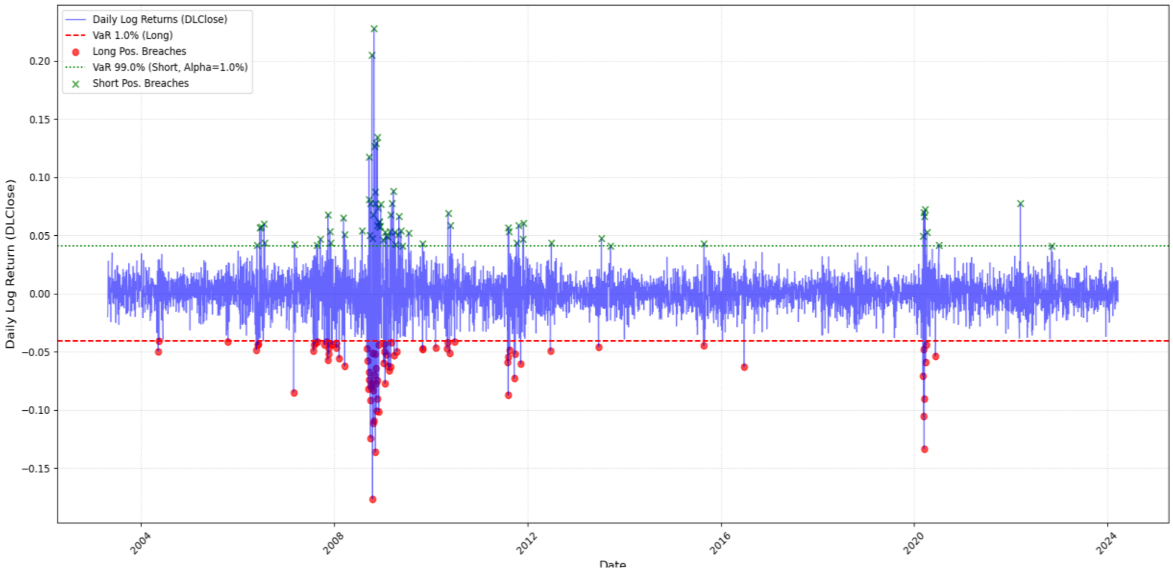
Venture into the application of other sophisticated AI methods, such as Convolutional Neural Networks (CNN), to these financial challenges.

Broaden our understanding by extending the scope of analysis to include a more comprehensive selection of emerging market ETF

Appendices

Appendices

Figure 1: In-Sample Parametric VaR (1% Alpha) Backtesting (EEM - Estimation Period).



Source: Outputs of the Python 3.1.

Table 1: Training LSTM Model (Improved and Corrected).

Epoch	Train Loss	Test Loss
10	1.000758	0.320674
20	0.998199	0.319309
30	0.985658	0.315901
40	0.981094	0.315410
50	0.959704	0.321006
60	0.935852	0.312873
70	0.901613	0.315596
80	0.874935	0.311804
90	0.857157	0.312447
100	0.837641	0.314634
110	0.808327	0.313629
120	0.796973	0.312458
130	0.784374	0.313014
140	0.773361	0.313944
150	0.745686	0.310298
160	0.735037	0.309687
170	0.713498	0.311702
180	0.701367	0.309971
190	0.687661	0.312188
200	0.677267	0.312543
210	0.676631	0.315540
220	0.648103	0.315251
230	0.650808	0.312750

240	0.641421	0.314343
250	0.602579	0.314569
260	0.595586	0.314250
270	0.579775	0.312450
280	0.565092	0.316354
290	0.548987	0.314560
300	0.532552	0.310925
310	0.518133	0.308642
320	0.503362	0.308224
330	0.496143	0.312054
340	0.481429	0.310457
350	0.466912	0.310455
360	0.460104	0.308819
370	0.448250	0.310939
380	0.433218	0.310023

Source: Outputs of the Python 3.13.

Table 2: LSTM Model Forecast Outputs for a 6-Month Horizon (127 Days).

Date	Actual Residual	Predicted Residual
2024-03-25	-0.000561	-0.000869
2024-03-26	-0.000700	-0.000641
2024-03-27	0.001692	-0.000152
2024-03-28	0.003787	0.000568
2024-04-01	0.002275	0.001122
2024-04-02	0.003450	0.000970
2024-04-03	0.001131	0.001014
2024-04-04	-0.003416	0.000677
2024-04-05	0.001694	-0.000249
2024-04-08	0.006649	0.000297
2024-04-09	0.007701	0.001362
2024-04-10	-0.012730	0.001710
2024-04-11	0.004581	-0.001504
2024-04-12	-0.023207	-0.000029
2024-04-15	-0.008470	-0.004128
2024-04-16	-0.015601	-0.002642
2024-04-17	-0.001668	-0.002009
2024-04-18	0.002872	0.000800
2024-04-19	-0.002902	0.001831
2024-04-22	0.010073	0.000406
2024-04-23	0.009435	0.001929
2024-04-24	0.004986	0.002195
2024-04-25	0.002675	0.001606
2024-04-26	0.011885	0.001190
2024-04-29	0.011077	0.002060
2024-04-30	-0.012353	0.002320
2024-05-01	-0.000604	-0.000208
2024-05-02	0.024888	-0.000540
2024-05-03	0.012586	0.002766
2024-05-06	0.002905	0.002452
2024-05-07	-0.005678	0.000904
2024-05-08	-0.000322	-0.000963
2024-05-09	0.002753	-0.001364
2024-05-10	0.002721	-0.000489

2024-05-13	0.007757	0.000025
2024-05-14	0.006365	0.000637
2024-05-15	0.011566	0.000548
2024-05-16	0.003422	0.000917
2024-05-17	0.005054	0.000307
2024-05-20	-0.003325	0.000182
2024-05-21	-0.006326	-0.000640
2024-05-22	-0.004362	-0.001285
2024-05-23	-0.007877	-0.000743
2024-05-24	0.001776	-0.000398
2024-05-28	-0.001332	0.001387
2024-05-29	-0.014874	0.001178
2024-05-30	-0.004914	-0.001905
2024-05-31	-0.010649	-0.001067
2024-06-03	0.009501	-0.001649
2024-06-04	-0.013392	0.002261
2024-06-05	0.015123	-0.001485
2024-06-06	0.005677	0.001034
2024-06-07	-0.009243	0.001770
2024-06-10	0.003834	-0.000937
2024-06-11	-0.009580	0.000715
2024-06-12	0.009074	-0.000816
2024-06-13	-0.001846	0.001841
2024-06-14	0.001800	0.000814
2024-06-17	0.005836	0.000610
2024-06-18	0.010391	0.001169
2024-06-20	-0.000535	0.001849
2024-06-21	-0.003274	0.000612
2024-06-24	-0.000775	-0.000608
2024-06-25	-0.002290	-0.000624
2024-06-26	-0.002436	-0.000656
2024-06-27	0.000362	-0.000631
2024-06-28	0.001922	-0.000070
2024-07-01	0.002634	0.000385
2024-07-02	0.003374	0.000573
2024-07-03	0.015052	0.000691
2024-07-05	0.005995	0.002208
2024-07-08	0.001357	0.001696
2024-07-09	0.003942	0.000758
2024-07-10	0.006325	0.000653
2024-07-11	0.006677	0.001008
2024-07-12	0.004964	0.001142
2024-07-15	-0.009975	0.000869
2024-07-16	0.004471	-0.001179
2024-07-17	-0.016264	-0.000220
2024-07-18	-0.010820	-0.001993
2024-07-19	-0.012083	-0.001396
2024-07-22	0.007492	0.000247
2024-07-23	-0.008481	0.002905
2024-07-24	-0.014893	0.000595
2024-07-25	-0.006735	-0.002710
2024-07-26	0.009607	-0.001736
2024-07-29	-0.002198	0.002509
2024-07-30	-0.004354	0.001676
2024-07-31	0.020600	-0.000034

2024-08-01	-0.014887	0.002366
2024-08-02	-0.015504	-0.000447
2024-08-05	-0.031935	-0.003442
2024-08-06	0.002418	-0.008003
2024-08-07	0.005323	0.001181
2024-08-08	0.024436	0.003851
2024-08-09	0.007729	0.004452
2024-08-12	0.005343	0.002184
2024-08-13	0.010880	0.001287
2024-08-14	-0.003531	0.001633
2024-08-15	0.010543	0.000828
2024-08-16	0.012549	0.001175
2024-08-19	0.011781	0.001727
2024-08-20	-0.006552	0.001530
2024-08-21	0.003366	-0.000096
2024-08-22	-0.012596	-0.000705
2024-08-23	0.015630	-0.001306
2024-08-26	-0.007419	0.000518
2024-08-27	0.001729	-0.000251
2024-08-28	-0.007321	-0.000328
2024-08-29	0.000573	-0.001267
2024-08-30	0.001296	-0.000258
2024-09-03	-0.019227	0.000563
2024-09-04	-0.002909	-0.002700
2024-09-05	0.000599	-0.000537
2024-09-06	-0.017843	0.001541
2024-09-09	0.005865	-0.002320
2024-09-10	-0.003513	-0.000114
2024-09-11	0.007743	0.000542
2024-09-12	0.008423	-0.000200
2024-09-13	0.006473	0.001833
2024-09-16	0.003716	0.001872
2024-09-17	0.001850	0.001478
2024-09-18	-0.003383	0.001082
2024-09-19	0.020656	0.000089
2024-09-20	0.000274	0.002498
2024-09-23	0.008622	0.001252
2024-09-24	0.033636	0.001070

Source: Outputs of the Python 3.13