INVESTIGATING THE EFFECT OF SINGLE STOCK FUTURES TRADING ON THE VOLATILITY OF UNDERLYING STOCKS MODERATED BY MACROECONOMIC FACTORS IN THE KENYAN MARKET.

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DECLARATION

I declare that this work has not been previously submitted or approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the dissertation itself.

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DEDICATION

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ABSTRACT

The introduction of Single Stock Futures (SSFs) in the Kenyan stock market aims to provide a tool for hedging, price discovery, and liquidity enhancement. SSFs are a tool for risk management, particularly investors hedging their positions in underlying market. SSFs also breed speculators which might lead to significant price fluctuations thus volatility. Volatility is one of the main drivers of trading, it influences investor confidence and overall stability of equity markets. The general objective of this study was to investigate if single stock futures (SSFs) trading affects the volatility of the underlying stocks in the Kenyan futures market (NSE NEXT). Specifically, the study sought to analyze the short-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE), to analyze the long-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE) and to examine the moderating effect of macroeconomic factors on the relationship between single stock futures (SSFs) and the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE). The study was guided by Efficient Market Hypothesis (EMH), Information Flow Hypothesis and Volatility Feedback Theory. This research adopted a positivist approach to ensure objectivity in addressing the research questions. The study used causal research design. The population of this study includes the 10 single stocks listed and trading on the NSE NEXT from 4th July 2019 to 31st July 2024. The study carried out a complete enumeration of the ten NSE NEXT listed firms that traded in single stock futures between 4th of July 2019 to 31st of July 2024. The study utilized secondary quantitative data obtained from the NSE and Central bank of Kenya (CBK). The data included daily closing share prices and trading volumes for both the underlying stocks and the single-stock futures market, inflation rate and interest rates. Observations cover two periods: January 2019 to June 2019, representing the pre-SSF phase (for stocks that began trading in July 2019), and July 2019 to July 2024 representing the post-SSF trading phase. The data was prepared using Microsoft Excel and analyzed using STATA 13. Exponential GARCH (EGARCH) model was used to measure volatility of the underlying stocks. Vector Auto Regression (VAR) model was employed to test the short-term and long-term causality between single stock futures trading and volatility of the underlying stocks. To validate the results and ensure robustness of the findings, this research employed various diagnostic tests including; ARCH test and t-test for EGARCH model, Unit root test, Granger causality test and cointegration test for volume turnover and VAR model. The study concludes that introduction of SSFs had a significant positive effect on stock return volatility and trading volumes for Safaricom and Equity Holdings, suggesting that SSF trading increased market activity and speculative behavior in the short run. The study also concludes that in the long term, the analysis identifies a significant negative effect of SSF trading on stock return volatility, implying a stabilizing influence of derivatives on price fluctuations over time. This is supported by the presence of significant error correction terms in VECM models for firms like Safaricom, KCB, and Equity Holdings, confirming long-run equilibrium relationships. Furthermore, the analysis of moderating effects highlights a significant positive interaction effect between inflation and SSF trading volume on stock return volatility. This indicates that inflation amplifies the volatility-inducing impact of SSF trading, particularly in speculative environments. The findings suggest that macroeconomic factors like inflation can alter the volatility dynamics induced by SSFs. Since inflation is found to intensify the volatility of stock returns in markets with SSFs, policymakers should consider implementing inflation-targeting measures to reduce uncertainty and stabilize the financial markets.

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LIST OF ABBREVIATIONS AND ACRONYMS

BAT: British American Tobacco

CBK: Central bank of Kenya

CBK: Central Bank of Kenya

CBOT: Chicago Board of Trade

CME: Chicago Mercantile Exchange

EGARCH: Exponential Generalized Autoregressive Conditional Heteroskedasticity

ESTAR: Exponential Smooth Transition Autoregressive

GARCH: Generalized Autoregressive Conditional Heteroskedasticity

LIFFE: London International Financial Futures Exchange

NSE: Nairobi Securities Exchange

SSFs: Single stock futures

VAR: Vector Auto Regression

VECM: Vector Error Correctiom Model

DEFINITION OF TERMS

Inflation rate	is the percentage change in the general price level of goods and services in an economy over a specific period, usually measured on an annual basis. It reflects how much prices have increased, indicating the rate at which the purchasing power of money is declining (Liu & Guo, 2021).
Interest rate	Refers to the cost of borrowing money or the return earned on savings or investments, expressed as a percentage of the principal amount, over a specific period (usually annually) (Mensi et al., 2021).
Macroeconomic factors	Are the broad, economy-wide influences that affect the performance and behavior of an entire economy, including all industries, businesses, and consumers. These factors are typically beyond the control of individual firms or investors but play a critical role in shaping market trends, financial performance, and investment decisions (Chuang et al., 2020).
Nairobi Securities Exchange (NSE)	is the principal stock exchange in Kenya and serves as a key platform for trading equity and debt securities in the country (Ahmed & Kumar, 2019)
Single Stock Futures (SSFs)	are standardized financial derivative contracts that obligate the buyer to purchase, or the seller to sell, a specific quantity of an individual stock (typically 100 shares) at a predetermined price on a specified future date (Aggarwal & Thomas, 2015).
Stock volatility	Refers to the degree of variation in a stock's price over time. It measures how much the price of a stock fluctuates—either up or down—within a given period (Thadavilli & Vang, 2021).
Trading volume	Refers to the total number of shares or contracts of a particular security (such as a stock or derivative) that are bought and sold during a specific period, typically a day (Tang et al. 2020).

Underlying stocks — Refer to the actual shares of publicly traded companies upon which financial derivatives—such as options, futures, or other contracts—are based (Wu et al., 2018)

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Financial derivatives have revolutionized the global financial markets, offering investors new avenues for hedging risks and enhancing portfolio returns. The concept of derivatives dates back to biblical times, specifically in Genesis chapter 29, around 1700 BCE. In this account, Jacob agreed to work for seven years as a form of payment for the right to marry Rachel, the daughter of Laban, effectively illustrating an early example of an option contract (Gitogo et al., 2013). Laban defaulted this option by giving Jacob his elder daughter Leah, but since Jacob preferred Rachel, he purchased another seven-year option which was exercised on expiry.

Derivatives, just from the name, refers to financial instruments that derive their value from underlying assets such as stocks, bonds, commodities, currencies, or market indices where market participants do not trade or physically exchange an asset but exchange at a future date (Lembang & Asri 2022). In their book of Trading and Pricing Financial Derivatives, Boyle and McDougall (2018) define financial derivative as an economic contract whose value depends on or derived from the value of an underlying asset. According to Saleh (2022), they are key tools for risk management, speculation, and price discovery in modern financial markets. Derivatives allow investors to hedge against price fluctuations, enhancing market efficiency and liquidity (Odipo et al., 2020). There are various types of derivatives including, forwards, futures, options, and swaps. This paper will focus on futures particularly single stock futures. The choice of futures is because the Kenyan derivatives market is only trading futures as of July 2024. The choice of SSF is to be able to examine each stock individually and not a basket of stocks. While forward contracts are customized between two parties and are tailor-made, futures refer to standardized, exchange-traded contracts that entail more transparency from the point of view of business transactions (Zai & Mansur, 2024). Options are derivatives entitling investors with the right but not the obligation to buy or sell assets, and swaps are designed to exchange a financial obligation (Ganai et al., 2023). Hence, they are very often used for interest rate hedging.

Derivatives have existed since ancient times, with the Mesopotamian grain contracts and commodity trading in medieval Europe among the early examples of derivatives. The modern markets for derivatives began to take shape with the establishment of the Chicago Board of Trade, generally referred to as the Chicago Board of Trade (CBOT), in 1848. Initially, it offered futures contracts on agricultural commodities. The Chicago Mercantile Exchange, popularly referred to as the Chicago Mercantile Exchange (CME), introduced financial futures in the 1970s (Till, 2013). Later came the London International Financial Futures Exchange, the London International Financial Futures Exchange (LIFFE), and the Tokyo Financial Exchange (Kupke & Lattemann, 2008). Global derivatives markets today consist of New York, London, and Tokyo, among many others. They come under the purview of the Commodity Futures Trading Commission in the U.S. and the Financial Conduct Authority in the U.K. In this way, they help in establishing transparency and stability. Major exchanges like CME, Intercontinental Exchange (ICE), and Euronext offer various derivative products, providing liquidity and risk management tools (Cantillon & Yin, 2011). Karanja (2016) indicates that in order for futures trading to be successful it has to take place in an active futures market and information must be widely available in this market in order for trade not to fail. Futures trading has proven not to be very successful in futures markets with very stringent government controls. A successful futures market also requires that there exists real economic risks that producers and users need to manage

South Africa leads the African continent in derivatives trading, with the Johannesburg Stock Exchange (JSE) launching its derivatives market in 2001 (Krüger, 2016). The JSE offers futures and options on equities, interest rates, and commodities, attracting institutional investors. Countries like Nigeria and Egypt have tried to introduce derivatives but face liquidity and regulatory challenges. Kenya is the only East African country with a structured derivatives market. Other countries in this region have not established similar markets due to market underdevelopment and regulatory limitations (Fassas & Siriopoulos, 2021). The NSE introduced Single Stock Futures trading in July 2019 as part of the NSE Derivatives Market NEXT, which became the second Exchange in Africa to offer SSFs (Fassas & Siriopoulos, 2021). The NSE NEXT market was designed to enhance capital markets, attract investor participation and provide risk management tools.

1.1.1 Stock Market Volatility

Stock market volatility refers to the degree of variation in the price of stocks or market indices over time. It is an important metric for investors and policymakers because very high volatility is often associated with higher risk, uncertainty, and potential losses in the market. There are three levels of volatility; low volatility which is associated with non randomness, hence predictability and inefficient stock market, normal or high volatility associated with randomness hence efficient stock market and lastly, excessive volatility which is associated with extreme randomness and hence not good in a stock market (Bhowmik 2013). The volatility of stock prices is influenced by various factors, including macroeconomic factors, investor sentiment, market liquidity, and the presence of speculative activities. It can manifest as either short-term fluctuations or as prolonged periods of instability that can disrupt market functioning (Kim et al., 2025). One key issue with stock market volatility is its potential to disrupt investor confidence. When volatility is excessive, it creates an environment of uncertainty, making it difficult for investors to predict future market conditions. This can deter investment, especially from risk-averse investors, and may lead to reduced market participation. In the case of the Nairobi Securities Exchange (NSE), excessive volatility could hinder the development of the market, dissuading institutional investors from participating and making it harder for companies to raise capital (Bouchouev et al, 2025).

Another problem associated with high stock market volatility is the increased risk of speculative bubbles. Speculation in the absence of sound market fundamentals can artificially inflate asset prices, creating price distortions. When the speculative bubble bursts, it can lead to sharp price corrections, further amplifying volatility and causing significant financial losses for investors (Cheng & Xiong, 2014). The introduction of financial derivatives such as Single Stock Futures (SSFs) has been proposed as a means of mitigating stock market volatility by providing a mechanism for risk management and price discovery. Futures markets are expected to improve market liquidity by allowing for increased trading volume and tighter bid-ask spreads. Additionally, the price discovery process in futures markets can help align stock prices with their fundamental values, reducing the occurrence of extreme price movements (Bahoo et al., 2020). However, the effect of SSFs on volatility remains a contentious issue. While some studies suggest that SSFs can stabilize markets by improving liquidity and enabling better price discovery (Kim et al., 2025; Bouchouev et al., 2025), others argue that they could exacerbate volatility, particularly in markets characterized by speculative trading and high leverage (Rao, 2025; Cheng & Xiong, 2014).

In the context of Kenya's emerging SSF market, where liquidity is still low, the risk of heightened volatility due to speculative trading is a valid concern. Without adequate safeguards, SSF trading could amplify price swings rather than mitigate them, especially during periods of heightened market uncertainty. Volatility has been a challenge in the equities market, In 2019-2020 financial year, volatility in the market performance was observed with the index plummeting to 1,942.12 as at the end of financial year (CMA 2020). Additionally, the NSE (2020) integrated report confirms the performance of listed securities was largely subdued in line with the performance of global markets characterized by sharp price volatility erratic demand and forecast challenges. The NSE acknowledges the challenge brought about by volatility, during the year 2023, the board adopted a diversified strategy to ensure the business remains adequately cushioned from market volatility as experienced in the last two financial years (NSE 2023).

Research by Ndwiga and Muriu (2016) examined time-series data from the NSE and found that introducing SSF contracts initially increased daily stock return volatility by 8.3%. However, as trading volumes increased and more institutional investors participated, volatility stabilized, leading to a 5.1% decrease in average daily price swings. Their study concluded that "while SSFs may induce short-term volatility spikes, their long-term effect smoothed price fluctuations" (Ndwiga & Muriu, 2016). Kalovwe, Mwaniki and Simwa (2021) also support the stabilization hypothesis, noting that increased market liquidity due to SSF trading reduced bid-ask spreads, making the market more efficient. Their findings suggest that stocks with active SSF contracts experienced lower price swings than non-SSF stocks, reinforcing that derivatives can enhance market stability when adequately regulated.

The debate on SSFs and volatility in Kenya reflects these contrasting perspectives. While some research suggests that SSFs could stabilize the market by attracting institutional investors and improving liquidity, concerns remain regarding the speculative nature of derivatives trading and the risk of price manipulation in a low-liquidity environment. Given the early stage of Kenya's

SSF market, further empirical research is required to assess whether SSFs trading lead to low, high or excess volatility. Understanding how SSFs affect NSE-listed stocks is crucial for policymakers, investors, and regulators seeking to foster a more stable and efficient derivatives market in Kenya.

1.1.2 Single-Stock Futures (SSFs)

Single-stock futures (SSFs) are a type of futures contract based on individual underlying assets. The World Federation of Exchanges describes an SSF as a standardized, tradable agreement obligating its holder to buy or sell a specific stock on a future date at a predetermined price. As noted by Khan and Abbas (2013) and Matlu and Arik (2015), SSFs are individual futures contracts tied to specific shares. They represent a leveraged position in underlying stock, funded entirely by debt and secured with a margin requirement typically fixed at 20% of the stock's value (Khan et al., 2011).

Single stock Futures made their initial appearance in the financial markets in the 1990s. Australia was the pioneer, launching SSFs on the Sydney Futures Exchange in 1996 (Khan & Abbas 2013). This innovation was then followed by other markets with Pakistani introducing SSFs on the Karachi Stock Exchange in 2001 ahead of many other countries including United Kingdom and Spain in 2001 and U.S. where SSFs were introduced on November 8, 2002, after Commodity Futures Modernization Act of 2000 (Khan et al., 2011). The introduction of SSFs has been met with mixed reactions regarding their impact on stock market volatility. Ahmed and Huo (2021) argue that SSFs contribute to market efficiency by enhancing liquidity, providing better price discovery mechanisms, and enabling more effective risk management strategies. Conversely, SSFs may lead to increased market volatility due to speculative trading and potential manipulation of stock prices (Habiba et al., 2020).

They provide hedging opportunities, leverage, and liquidity, making them valuable instruments for risk management and speculation (Hull, 2017). Unlike traditional stock investments that require an entire capital outlay, SSFs allow traders to control more prominent positions with smaller margin deposits, amplifying gains and risks. Additionally, SSFs enhance price discovery by reflecting market expectations of stock price movements, helping investors make informed trading decisions (Bodie et al.,, 2021). However, SSFs also pose risks, particularly in speculative trading, which can contribute to increased short-term volatility.

SSFs have been widely adopted in developed markets, where they are traded alongside index futures, stock options, and other equity-linked derivatives. Exchanges such as the Chicago Mercantile Exchange (CME) and the London International Financial Futures Exchange (LIFFE) facilitate SSF trading under strict regulatory oversight to ensure fair pricing and investor protection (Bae et al., 2004). Studies indicate that SSFs contribute to market efficiency by enhancing liquidity, improving risk-sharing mechanisms, and strengthening price discovery processes (Antoniou et al., 1998). However, some scholars argue that SSFs can also lead to excessive speculation, particularly in markets with high leverage and low investor education (Ahmed & Kumar, 2019). Therefore, it is correct to conclude that some uncertainties are associated with SSFs.

In Africa, the development of financial markets has been uneven, with some countries embracing sophisticated financial instruments while others lag. South Africa, for instance, has a well-developed derivatives market, including SSFs, which have been traded since 2001. Studies on the South African market (Atenga & Mougoué, 2021; Khan, 2023; Marozva, 2020) have provided insights into the effects of SSFs on market volatility, with mixed results. As such, the African context presents unique challenges and opportunities, making examining the impact of financial innovations like SSFs in different African markets essential. Kenya, as one of the leading economies in East Africa, has been progressively developing its financial markets. The Nairobi Securities Exchange (NSE) is a pivotal institution in the region, playing a crucial role in capital formation and economic development (Monicah & Shiundu, 2020; Makau, 2021). The NSE introduced Single Stock Futures trading in July 2019 as part of the NSE Derivatives Market *NEXT* becoming the second Exchange in Africa to offer SSFs. A study by Kalovwe, Mwaniki and Simwa (2021) alluded that the introduction of SSFs in Kenya represents a significant milestone in the evolution of its financial markets. However, the trading of SSFs on market volatility in the Kenyan context calls for a comprehensive analysis to understand their implications for market stability and investor analysis.

The debate on the role of SSFs in financial markets remains a crucial topic for researchers and policy-makers worldwide. Studies examining the Nairobi Securities Exchange (NSE) and its derivatives counterpart, NSE NEXT, have produced mixed findings, reflecting the complexities of Kenya's emerging derivatives market. Some studies argue that SSFs have contributed to increased short-term volatility. Raubenheimer (2019) found that introducing SSFs at NSE NEXT led to heightened volatility in the underlying stocks, particularly those with lower liquidity. His research suggested that speculative trading among retail investors played a role in price swings, stating that "the presence of futures contracts encouraged short-term speculation rather than stabilizing stock prices."

Similarly, Muthenya (2020) analyzed NSE NEXT trading data over one year and reported that stocks with active SSF contracts experienced an 11.7% higher volatility than those without. His research attributed this to low market liquidity and speculative trading, particularly by retail investors using highly leveraged positions. "The limited depth of the Kenyan derivatives market," Muthenya argued, "magnifies the price fluctuations of the underlying stocks, making SSFs a potential driver of instability rather than a stabilizing instrument" (Muthenya, 2020). Further, Cheng & Xiong (2014) found that stocks with SSFs listed on NSE NEXT exhibited a bid-ask spread reduction of 4.9%, indicating that liquidity improved in these stocks. However, Cheng & Xiong (2014) also noted that intraday volatility was 6.2% higher on average in SSF-listed stocks than in non-SSF stocks, suggesting that while SSFs improve liquidity, they can amplify short-term price swings. His study recommended strengthening regulatory oversight to reduce excessive speculation and promote institutional participation in SSF trading. This research was carried out in 2020 just a year or less after SSF introduction, a lot has changed since then. It poses the question, does the market hold the same standing as it did in 2020? Is there need for a more recent study to understand the current effect of SSFs on stock market volatility?

Kalovwe, Mwaniki and Simwa (2021) research offers a more neutral perspective, analyzing the trading volume and return volatility of the NSE 25 Index Futures and SSFs. They found that volatility persistence was reduced by 3.8% after six months of active SSF trading, with their model suggesting that the stabilizing effect of SSFs is only realized once trading volumes reach a certain threshold. Their findings imply that SSF trading may initially contribute to price swings, but as market participation increases, volatility stabilizes.

Overall, the debate on SSFs and volatility in Kenya remains unresolved. While some research identifies short-term speculative effects, others highlight the long-term benefits of SSFs in enhancing price discovery and reducing extreme volatility. The nascent state of Kenya's derivatives market, along with low liquidity and regulatory constraints, suggests that further empirical research is needed to fully understand the dynamics of SSFs on the volatility of NSE-listed stocks.

1.1.3 Macroeconomic Factors

Macroeconomic factors play a fundamental role in shaping the behavior of financial markets, influencing both investor decision-making and asset price dynamics. Among the most influential macroeconomic indicators are the inflation rate and the interest rate, both of which have profound implications for stock market performance and volatility. Their relevance becomes even more pronounced in the context of emerging financial instruments such as Single Stock Futures (SSFs), which are increasingly being adopted as tools for hedging, speculation, and price discovery in markets like the Nairobi Securities Exchange (NSE) (Madura, 2020; Wanjiku & Muturi, 2019).

Inflation rate, representing the rate at which the general level of prices for goods and services is rising, affects the purchasing power of money and introduces uncertainty into financial systems. For investors, high or volatile inflation can reduce the real returns on investment, prompting adjustments in portfolio strategies (Fama, 2022). Inflation impacts stock prices by altering discount rates applied to future cash flows and influencing corporate profitability through increased input costs. Consequently, the volatility of stock returns may rise during inflationary periods due to greater uncertainty in earnings expectations and valuation models (Boyd et al., 2001). Within the context of SSFs, inflation can influence how aggressively investors use

derivatives for hedging or speculative purposes, potentially moderating the relationship between futures trading and stock volatility (Osei-Wusu & Twenefour, 2018).
On the other hand, the interest rate, often operationalized through the central bank's benchmark rate (such as Kenya's Central Bank Rate), influences the cost of borrowing, capital flows, and the broader economic environment. Higher interest rates increase the opportunity cost of holding equities, typically leading to downward pressure on stock prices and changes in investment behavior (Mishkin, 2016). Moreover, interest rates directly impact the pricing of derivative instruments like SSFs through the cost-of-carry mechanism, which links futures prices to the spot price, interest rates, and dividends (Hull, 2018). As a result, fluctuations in interest rates can affect both the volume and nature of SSF transactions, and in turn, influence the volatility of the underlying stock prices. Investors may shift strategies in response to interest rate movements, altering market dynamics and introducing new patterns of volatility (CBK, 2023; CMA, 2022).

1.1.4 NSE/NSE NEXT

The Nairobi Securities Exchange (NSE) is Kenya's blue-chip stock exchange and a significant player in developing capital, price discovery, and market liquidity. As a base marketplace, NSE provides a platform for trading publicly traded stocks, bonds, and traded exchanged funds (ETFs). NSE encourages investment and wealth creation and is a performance indicator in a country's economy. Over the years, NSE has expanded, with both domestic and international investors investing in Kenya's lucrative financial marketplace. However, like most emerging economies, NSE has previously grappled with liquidity, price volatility, and efficiency in its markets. NSE is sensitive to macroeconomics, investors' moods, and events in terms of regulators and is, therefore, susceptible to fluctuations in price and liquidity. One of NSE's most significant weaknesses in the years preceding 2019 was a lack of organized instruments for managing risk, which investors could use to hedge price fluctuations. That weakness saw NSE introduce NSE NEXT, Kenya's first organized derivatives marketplace, to back NSE with a platform for offering future contracts for price discovery, speculating, and hedging.

The NSE NEXT, a derivatives market, was introduced in July 2019, introducing SSFs and Index Futures, with the view to increasing sophistication in Kenya's financial markets. It was constructed to complement NSE with a future contract for price discovery improvement, speculating, and hedging to bridge such a gap. Thus, it contributed significantly to increasing market liquidity, price discovery, and risk management thus positioning Kenya in the current trends in global financial markets (Kalovwe et al., 2021). Derivatives scope out the necessary tools for efficiency and stability in the market; they allow investors to hedge against volatility and trade on leverage speculation. The development of Kenya's derivative market is part of broader capital market reforms to modernize financial trading. At the international level, leading exchanges such as the Chicago Mercantile Exchange, London Stock Exchange, and Euronext have developed elaborate frameworks for derivatives that guarantee effective risk transfer and investment strategies (Kalovwe et al., 2021). These markets have emphasized effective regulation, transparency, and investor education supporting active derivatives trading.

South Africa initially experienced increased volatility in its market due to futures trading and later on there was enhanced liquidity and reinforced price discovery mechanism processes (Hull, 2017). Against this background, South Africa, with its maturely regulated environment that also enjoys dynamic institutional participation in the market, could be a benchmark for Kenya in handling market volatility, market liquidity or regulatory oversight and the challenges attributed to them but Kenya has completely different geographical, economic and political factors and policies that could deter it from relying on the South African market.

Since 2019, NSE NEXT has grown gradually, admitting listings for SSF trading for 10 companies, including Safaricom, KCB, Equity Bank, and East African Breweries Limited (EABL) (Kalovwe et al., 2021). Generally, the introduction of SSFs on NSE NEXT was a milestone in Kenya's financial market development. On one hand, SSFs have been instrumental in hedging and speculation, but ambiguity exists in their effect on the volatility of stocks. There is also mixed evidence from international studies; some viewed SSF as a stabilizer of markets, and others associated it with market volatility since it breeds speculators. Given Kenya's peculiar market structure and regulatory framework, this study was carried out to determine whether SSF trading significantly affects the volatility of the underlying stocks. The Kenyan derivatives market is still in its infancy; hence, minimal empirical evidence exists on how SSFs influence the movement of stock prices.

1.2 Problem Statement

The introduction of Single Stock Futures (SSFs) in the Kenyan stock market (NSE NEXT) aims to provide a tool for hedging, price discovery, and liquidity enhancement. SSFs are a tool for risk management, particularly investors hedging their positions in underlying market. SSFs also breed speculators which might lead to significant price fluctuations. Volatility is one of the main drivers of trading, it influences investor confidence and overall stability of equity markets. High volatility leads to market efficiency as price fluctuates at normal rates thus attracting investors, low volatility leads to lack of randomness hence reduced trading activity, excess volatility leads to abnormal price fluctuations hence investors leave the market due to extreme risk (Yadav 2017). It is therefore important to understand the effect SSF trading has on volatility. There is considerable uncertainty regarding SSFs effect on the volatility of the underlying stocks, especially considering the speculative nature of futures trading and the nascent state of Kenya's derivatives market. While financial derivatives like SSFs are designed to stabilize markets by enabling better risk management, their effect on stock market volatility, particularly in emerging markets, is still contentious.

The volatility of stocks listed on the Nairobi Securities Exchange (NSE) is a key concern for investors and policymakers. Historical data reveals that the stock market in Kenya has experienced several periods of very high volatility, especially during economic shocks or market-driven events. For example, between 2018 and 2020, the NSE-20 Index saw a sharp increase in volatility, with the standard deviation of daily returns rising by 7.2%, compared to a 3.5% increase in the previous five years (NSE, 2021). This heightened volatility has been attributed to various factors, including political uncertainty, macroeconomic factors, and investor sentiment, but the introduction of SSFs as a financial instrument may have added a new dimension to this volatility. Given the early stage of Kenya’s SSF market, the effect of SSF trading on the underlying stock volatility remains unclear

Globally, studies have produced mixed findings on the relationship between SSFs and stock market volatility. Some research suggests SSFs can stabilize markets by providing additional liquidity and improving price discovery (Habiba et al., 2020). Additionally, Asgharian *et al*. (2023) investigated the Turkish market and observed that the introduction of SSFs led to a reduction in spot market volatility. In contrast, other studies indicate that SSFs may contribute to increased volatility due to speculative trading and market manipulation (Ahmed & Huo, 2021; Mensi et al., 2021). In the Chinese market, which is characterized by high retail investor participation and relatively less mature regulatory frameworks, the introduction of SSFs has been linked to increased spot market volatility. Guru and Yadav (2023) argued that the speculative nature of many retail investors, combined with the rapid dissemination of information through futures trading, can lead to excessive price swings and market instability. This highlights the importance of considering market-specific factors, such as investor composition and regulatory oversight, when assessing the impact of SSFs.

Most studies have focused on more developed markets (Khan, 2023; Marozva, 2020). The divergent findings underscore the need for context-specific analysis, particularly in emerging markets like Kenya. Previous research provides some insights, but Kenya's unique economic, regulatory, and market structures necessitate a separate investigation. The introduction of SSFs in Kenya's NSE *NEXT* is relatively recent, and there is need for empirical evidence on the possible effects of SSFs trading on underlying market volatility. Therefore, this study sought to fill the gap in the literature by examining the impact of Single-stock future trading on the volatility of underlying market in Kenya. This research provides crucial findings on the relationship between SSFs trading and volatility of the underlying stock market which is useful to the stakeholders at the NSE as well as the *NEXT*.

1.3 Objectives of the Study

1.3.1 General Objective

The general objective of this study was to investigate the effect of single stock futures (SSFs) trading on the volatility of the underlying stocks in the Kenyan futures market (NSE *NEXT*).

1.3.2 Specific Objectives

i. To analyze the short-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE)

ii. To analyze the long-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE)
iii. To examine the moderating effect of macroeconomic factors on the relationship between single stock futures (SSFs) and the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE)

1.4 Research Questions

i. What is the short-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE)
ii. What is the long-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE)
iii. What is the moderating effect of macroeconomic factors on the relationship between single stock futures (SSFs) and the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE)

1.5 Scope of the Study

This study focused on investigating effect of single stock futures (SSFs) trading on the volatility of the underlying stocks in the Kenyan futures market (NSE NEXT). Specifically, the study sought to analyze the short-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE), to analyze the long-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE) and to examine the moderating effect of macroeconomic factors on the relationship between single stock futures (SSFs) and the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE). The analysis included data on trading volumes, price discovery, inflation rates and interest rates. The population of this study includes the 10 single stocks listed and trading on the NSE NEXT from 4th July 2019 to 31st July 2024. Kothari (2004) emphasizes that there is no need to carry out a sample survey when the population is small. This study therefore carried out a complete enumeration of the ten NSE NEXT listed firms that traded in single stock futures between 4th of July 2019 to 31st of July 2024. Geographically, the study is confined to Kenya but draws comparisons with other African markets where relevant.

1.6 Significance of the Study

Understanding the relationship between SSFs trading and stock market volatility is crucial for general investors, policy/market makers, market participants and academicians to make informed decisions and to ensure the stability and development of the Kenyan financial markets. The research contributes to the broader discourse on the role of financial derivatives in emerging markets, providing valuable insights for other African countries considering similar financial innovations.

1.6.1 General Investors

The research provides general investors with valuable insights into how SSF trading activities influence market dynamics. Understanding the relationship between SSF trading volume and volatility, helped investors make more informed decisions regarding their trading strategies and risk management. By gaining a clearer picture of how SSF trading affects the underlying spot market, investors can better anticipate market movements, optimize their investment portfolios, and enhance their overall returns.

1.6.2 Nairobi Securities Exchange

This research offers critical data and analysis that can guide the NSE on development of its financial products and services. By understanding the effects of SSF trading on market volatility, the NSE can make informed decisions about introducing or modifying SSF products. This leads to improved market efficiency and attractiveness, thereby enhancing the exchange's competitiveness and appeal to both local and international investors. Moreover, the findings help the NSE in designing better regulatory frameworks and operational strategies to ensure market stability and growth.

1.6.3 Financial Market Regulators

Financial market regulators benefits significantly from this research by gaining empirical evidence on the impact of SSF trading on market performance. The insights into how SSF trading influences market volatility enables regulators to craft more effective policies and regulations to mitigate risks associated with derivative trading. Gaining insights into these dynamics enables regulators to promote fair and transparent market practices, safeguard investor interests and uphold stability and integrity of financial markets. The research findings serves as a basis for refining existing regulations and introducing new ones that better align with market realities.

1.6.4 Academics

Academicians find this research valuable as it adds to the body of knowledge on the interactions between derivative markets and spot markets. The detailed analysis of SSF trading impact on spot market performance provides rich datasets and new insights that can be used for further academic inquiry and research. This study serves as a reference point for developing new theories and models related to financial market behavior and efficiency. Additionally, the findings can be incorporated into academic curricula, enhancing the educational content and providing students with up-to-date empirical evidence and real-world applications of financial theories.

1.7 Chapter Summary

This section presents the chapter one summary which comprises of the background of the study on the effect of single stock futures trading on the volatility of underlying stocks, statement of the problem, objectives of the study (general and specific objectives), research questions, scope of the study and the significance of the study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section examines the key theories on stock market volatility that serve as the foundation for this research. Beyond the theoretical perspectives, it also analyses extensive studies conducted by various authors on stock market volatility and the influence of single-stock futures trading on the volatility of underlying stocks. Different measures of volatility are explored, culminating in development of a conceptual framework. The chapter is structured as follows: 2.2: Theoretical Review; 2.3: Empirical Review; 2.4: Conceptual Framework and Operationalization of Variables.

2.2 Theoretical Review

This research adopted a multi-theoretical approach to analyse stock volatility, encompassing characteristics such as price fluctuations, market sentiment, trading volume and measurement. The study will investigate both the short-term and long-term impacts of derivatives on the volatility of underlying stocks, with the efficient market hypothesis (EMH), information flow hypothesis, and volatility feedback theory forming its theoretical foundation. The EMH offers insights into the market sentiment aspect of volatility, which in this research is assessed using trading volume. Furthermore, the volatility feedback theory provides additional context for understanding the role of trading volume in stock volatility.

2.2.1 Efficient Market Hypothesis (EMH)

Fama (1970) introduced the efficient market hypothesis (EMH), which examines stock market prices in relation to the information available in the market. The theory asserts that security prices at any given time should reflect all currently available information in an unbiased manner, and the returns earned should align with the associated level of perceived risk. Since the stock prices reflect all the publicly available information, it is impossible to beat these stock prices from a performance perspective of the long run i.e. technical analysis cannot be used to predict the randomness of the future. An efficient capital market is one in which security prices adjust rapidly to the arrival of new information (Naseer et al., 2016). Since SSFs improve the overall information flow in the market, price discovery for the underlying stock is enhanced. Amihud and Mendelson (1986) suggest that short-term investors are more inclined towards volatile stocks compared to long-term investors due to transaction costs, leading to market segmentation. According to EMH, it is impossible to consistently outperform the market on a risk-adjusted basis because stock prices already incorporate and respond to new information efficiently. Fama (1970) identified three relevant subsets of this hypothesis: The weak form posits that all past trading information is fully incorporated into stock prices. The semi-strong form assumes that all publicly available information is reflected in stock prices. Finally, the strong form asserts that stock prices account for all information including both public and private data.

In the context of SSFs, the EMH suggests that futures trading should increase market efficiency by improving the incorporation of information into stock prices, potentially reducing volatility. By making relevant information more readily available, SSF trading reduces information asymmetry which in turn decreases speculation based on incomplete information, thus reducing the likelihood of sudden, large price swings. Empirical studies in developed markets have provided mixed results. Antoniou, Holmes and Priestley (1998) found that the introduction of SSFs improved the price discovery process and enhanced market efficiency. However, critics argue that SSFs can increase speculation, which might lead to short-term volatility spikes, especially in less liquid markets (Chakrabarti, 2010). In an efficient market, SSFs should help stabilize prices by allowing investors to hedge risks effectively. However, in an emerging market like Kenya, SSF trading could either enhance efficiency or exacerbate price fluctuations due to speculative trading owing to the lower liquidity and higher informational asymmetries (Mwangi, 2022).

This theory is relevant to the study as it explains the price discovery processing the stock market based on publicly available information – a key dimension of volatility measured through trading volume. However, its limitation lies in the assumption that all investors are well informed, skilled and capable of continuously analyzing new information. Still, the majority of common investors are not trained financial experts, hence must be complemented with another theory that takes into account clustered volatility which proves that markets are not perfectly efficient and individual market prices can't be independent of each other. The effect of SSFs trading on the price discovery aspect of underlying stock volatility in the Kenyan stock market was assessed in this research.

2.2.2 Information Flow Hypothesis

Bae, Kwon and Park, (2004) came up with the Information flow hypothesis which looks at the information distribution and volatility of assets and stocks arguing that derivatives markets, such as SSFs, facilitate the faster dissemination of information, thus contributing to more efficient markets. This theory posits that the introduction of futures trading enhances price discovery, as futures prices reflect expectations of future spot prices based on current and anticipated information (Bae et al., 2004). By revealing market sentiment and expectations about future stock performance, SSFs provide an additional channel for the rapid incorporation of information into stock prices.

Information dissemination through SSFs could also amplify noise trading—speculative trading that is not based on fundamentals but rather on short-term price fluctuations (Silva, 2019). This could lead to increased volatility, especially if market participants overreact to short-term information. Thus, the Information Flow Hypothesis suggests that SSFs could have a dual impact: they may improve market efficiency by enhancing price discovery but also contribute to short-term volatility through speculative trading.

Empirical studies provide substantial support for this hypothesis, indicating that futures markets often lead spot markets in price discovery. Figlewaski (1981) argued that speculation in derivatives markets transmits to underlying spot markets, introducing destabilizing forces and potentially causing undesirable price bubbles. Ross (1989) asserted that the variance in price changes corresponds to the rate of information flow heightens asset price volatility. Thus, if derivatives markets enhance information flow, spot price volatility must adjust accordingly, barring arbitrage opportunities.

Futures market activities amplify spot price variability when futures prices are influenced by technical factors or manipulations (Kmara et al., 1992). Additionally, hedging pressures in futures markets spill over into spot markets as traders transfer risk between the two. Chatrath et al. (1996) examined the link between volatility and trading volume, finding that increased trading volume leads to heightened volatility in exchange rates, using the GARCH (1,1) model.

Adrangi and Chatrath (1998) explored the relationship between exchange rate fluctuations and the number of contracts held by traders, concluding that speculative traders drive market volatility. Bhargava and Malhotra (2007) analysed futures trading in four currencies from 1982 to 2000, discovering that day traders and speculators destabilized the futures market, though the role of hedgers remained unclear. Sharma (2011) investigated the connection between spot market volatility and trading activity in currency futures, finding that spot exchange rate volatility increased after the introduction of currency futures. Finally, Goyal and Mittal (2014) studied the impact of currency futures on USD/INR exchange rate volatility. Their findings revealed that the introduction of currency futures in India led to an increase in spot market volatility for the USD/INR exchange rate.

In the Kenyan context, the introduction of SSFs could help bridge the information gap by incorporating broader market expectations into stock prices more quickly. However, whether the market is mature enough to handle this additional information flow efficiently remains an open question.

The limitation of this theory is that it presumes that new information is always fully reflected in market prices. Yet one can observe prices fluctuating (sometimes very dramatically) every day, hour, and minute. Since real world markets have hidden complexities such as time of expiration and volatility of the asset, this theory was complemented with another theory that takes into account clustered volatility.

2.2.3 Volatility Feedback Theory

Schwert, and Stambaugh (1987) developed the volatility feedback theory, which looks at how volatility itself can influence asset prices. According to this theory, when volatility increases, it raises the risk perceived by investors, leading to a drop in asset prices as investors demand higher returns for bearing additional risk. In the case of SSFs, this theory suggests that increased volatility in the underlying stocks may lead to increased SSF trading, which, in turn, could further amplify volatility, creating a feedback loop. Empirical evidence from emerging markets shows that the introduction of futures trading can sometimes increase volatility rather than reduce it, particularly in the early stages of market development (Kumar & Seppi, 1994). Futures markets can attract speculators who increase trading volume, but this can also lead to price destabilization if it encourages excessive risk-taking (Singh, 2015).

The feedback loop between volatility and futures trading is especially pronounced in markets with lower liquidity and higher speculative activity. For example, in the Brazilian market, Silva (2019) found that volatility increased following the introduction of SSFs due to increased speculative trading. In Kenya, where the market is still developing, the Volatility Feedback Theory may suggest that SSF trading could lead to higher volatility in the short term as investors adjust to the new financial instrument. This theory is relevant to the study of impact of single stock futures trading on volatility of underlying stocks in the Kenyan futures market as it can be applied well in less mature markets and less liquid markets where volatility tends to be higher.

2.3 Empirical Review

Over the past decade, the relationship between single stock futures (SSFs) and the Volatility of the underlying stocks has been a topic of considerable empirical investigation. SSFs, which allow investors to hedge, speculate, or enhance liquidity, have raised questions about their potential to either increase or decrease the Volatility of stocks. This section reviews the existing research on the topic of the Impacts of Single Stock Future Trading on the Volatility of the underlying stock, establishes the current state of knowledge, and contextualizes the present study. It focuses on research published addressing how single stock futures impact the Volatility of the underlying stocks, both short- and long-term, in the Kenyan market and markets around the globe. To do this, this review categorizes these empirical studies into three main themes. First, it explores research done on the impacts of SSFs trading on volatility of underlying stocks both before and after the introduction of SSFs. Second, it examines studies of short-term effects and, lastly, the long-term effects of SSFs trading on the Volatility of the underlying stocks.

2.3.1 Impacts of SSF Trading on Volatility of the Underlying Stocks

Several studies have researched the impact of futures trading on volatility of stock market but their findings are not in agreement. Aggarwal and Thomas (2015), in their study on the Indian market to examine volatility pre- and post-SSF introduction in India, an emerging market with high retail investor participation, studied volatility (measured using daily standard deviation) since the introduction of SSFs (binary variable), trading volume, market capitalization. They found that introducing SSF increased volatility for small-cap stocks but had a marginal effect on large-cap stocks. This was attributed to heightened speculative trading, particularly by retail investors who leveraged the low-margin requirements of SSFs. Similar findings were reported by (Wu et al., 2021) in China, where retail investors dominated. This aligns with the "increased volatility hypothesis", suggesting that speculative behaviour magnifies price fluctuations in less regulated or nascent markets. However, other than the geographical difference, it is essential to note that these experts had some gaps in their research and data. First, 95% of Indian companies are considered small-cap. Hence, it is impossible for their research and data to provide a conclusive review on both small-cap and large-cap stocks for the Indian market. Hence, it is safe to assume that the conclusive report they provided on large-cap stocks was theoretical.

Hung, Lee and So (2003) employed the Golsten J & R-GARCH (1,1) model to examine the influence of foreign-listed single-stock futures on the volatility of domestic underlying stocks in the Chinese stock market. Their analysis incorporated SSF trading activity variables, specifically SSF volume and open interest, into the variance equation of the model. These variables were decomposed into expected (informationless) and unexpected (volume shocks) components using ARMA models. The findings revealed that expected components of futures trading positively impacted volatility, whereas the unexpected (informationless) components reduced volatility in the underlying domestic stocks. This study did not encompass the main limitation of the GARCH model, inability to capture the leverage effect. First, the GARCH model is limited in providing a forecast on long-term horizons. This is because the model assumes that the volatility of information remains constant, which is untrue. The market changes constantly depending on certain variables. Secondly, the model does not account for structural breaks such as recession or a financial crisis. This point builds up on the fact that the model assumes a constant state, which does not apply to reality. If an economy encounters a financial crisis, it’s likely to impact the volatility of SSFs. Lastly, the model employs past information to make future predictions. This causes an invariance in situations where the past and future are non-linear. As a result, the model lacks some form of flexibility to incorporate some discrepancies that can impact volatility and

SSFs. Hence, it might be unwise to fully employ the conclusions reached by these experts that utilized the model as a point of argument.

Thadavilli and Vang (2021) examined the impact of singe-stock futures on the volatility of underlying stocks in Russian stock market. Using a sample of five stocks and applying the GARCH methodology, they observed that the introduction of SSFs had a somewhat positive-to-mixed effect on trading volume. They found that periods of prolonged high volatility led to increased SSF usage. Additionally, their analysis indicated a reduction in the overall long-term volatility of stock returns for the sample after the introduction of SSFs. They recommended further research into the mechanisms behind the reduced volatility and the effects of restrictions on short-selling. From this study, it is imperative to determine that introduction of SSFs provides standardizations in stock trading. However, the study failed to capture the aftermath of biased information flow, which is very prevalent. As determined, GARCH methodology is very linear in its predictions and is dependent on constant flow of events. It does not capture invariances that may occur in the market. Additionally, the sample size used for the study is low and cannot be used to make quantified judgement on market volatility and SSFs. The experts utilized five stocks. There is a chance that they might have missed invariances that occur on most SSFs hence affecting market volatility. Therefore, this study is limited to the model utilized and the research pool.

Wu, Zhang and Wu (2021) also, through their research on the Chinese stock market, investigated the impacts of the introduction of SSFs, turnover ratio, and market depth on the realized stock volatility and found that post-SSF introduction, volatility spiked, especially in sectors with high trading activity (e.g., technology). They used regression analysis with sector-level data to evaluate the impact of volatility. Regulatory gaps allowed speculative behaviour to thrive.
In Japan, (Liu et al., 2021), through their research on Japanese markets, evaluated SSF activity, turnover ratios, sector-specific characteristics and realized sectorial volatility using multivariate GARCH models. The study found increased volatility in the technology and energy sectors but decreased volatility in utilities and consumer staples. The main gap in this study is that it focuses on specific markets i.e technology. While specificity is essential while dealing with niches, it is somewhat redundant when it has to deal with general understanding of SSF and market volatility.

Additionally, they focused on impact of SSF introduction to specific area i.e Japan and China. It is essential to note that SSF impact varies across various countries depending in different countries. For example, in Kenya, post SSF has been attributed to stable stock trading. This is because, the stock information is available without bias and there's limited spot prices. Additionally, this stability varies across different sectors in the market. Hence, it is impossible to make a conclusive stance based on researching a particular sector. Additionally, they have employed some linearity to their assumptions and conclusions. Therefore, the main disparity of this study is the use of sectoral findings to make a conclusive stance on the impact of SSF introduction and market volatility.

Ahmed and Kumar (2019), using the Golsten J & R-GARCH (1, 1) model in their study, examine whether an impact on the underlying stock volatility in South Africa has been observed upon introducing stock exchange futures in their market. They looked at stock price volatility (measured via historical variance) since SSF introduction, market depth, and trading frequency. Their findings revealed increased volatility for small-cap stocks with low liquidity but decreased volatility for large-cap stocks with high institutional investor participation. The main gap in this study is the utilization of a historical variance and the expectation of linearity in SSF. As of 2021, stock-price volatility was recorded at 23.37. This is significantly high and is majorly attributed to inflation and fluctuation in the South-African stock market. As a result, there is a concept of non-linearity brought about by the fluctuations and inflations in the market. Additionally, with the occurrence of world-pandemic, the stock market was significantly impacted, a factor that was not pre-determined by the experts. Hence, the study does not account for structural changes.

Beer (2012) analysed the relationship between the introduction of single-stock futures contracts and price volatility in the South African market using the GRACH (1,1) methodology. The study found a significant reduction in both the level and structure of price volatility for underlying stocks. Similarly, Khan (2007) reported a decline in volatility for underlying stocks in the Indian market following SSF introduction, though there was a noticeable shift in trading volumes from the spot market to the SSF market. This study utilizes a limited data pool for research. They took into account a couple of stocks for analysis and conclusion. This leaves a significant pool of unstudied information. Additionally, it utilizes linearity to make conclusive findings. This is a

limitation in the sense that it does not account for structural changes like financial crisis. Hence, the conclusions of these experts could not be utilized comprehensively.
Kao, Chuang and Ku (2020) conducted a study to examine return and trading volume as well as return volatility and trading volume. They analyzed the asymmetry of contemporary and lead lags in the study of S&P 500 VIX Futures using the GJR-GARCH model. The key conclusions show that threshold effects are present in both the lead-lag and contemporaneous links between volatility-volume and return-volume. Furthermore, there are delayed effects from trading volume to returns and return volatility that range from one trading day to three trading day lags. While a bigger trading volume helps investors make money, it also increases volatility. The utilization of the KSS non-linear stationery test in the study provides a significant limitation, reliance on an approximation of the Exponential Smooth Transition Autoregressive (ESTAR) process. When handling complex nonlinearities, especially in financial data with near unit root characteristics, this can result in decreased power, which could lead to inaccurate conclusions about stationarity. Additionally, selecting the right transition parameter can be difficult and could affect test results.

Tang, Xiao and Wahab (2020) studies how oil futures price information can be used to US stock market volatility. The study utilizes the HAR framework and in-sample data in their investigation. Initially, during the in-sample period, the model's fit quality may be marginally enhanced by fluctuations in the oil market. It implies that knowledge on oil market volatility could be useful in predicting the volatility of the US stock market. Oil's daily actual volatility (RV), weekly RV, and monthly RV all have different effects. Furthermore, it is evident from out-of-sample data that the knowledge on oil price volatility enhances the prediction of volatility in the US stock market. Third, our HAR model with many variables performs better than the one with only one variable. It suggests that predicting the volatility of the US stock market can be aided by the synchronous relationships between the oil and stock markets. The study's conclusions are useful to scholars, investors, and legislators since volatility is a crucial component of risk management, hedging tactics, and portfolio selection. The main gap in the study is the focus on area-specific sectors in stock markets. Hence, the information in the article is only applicable to the oil industry.

Liu and Guo (2021) examined the forecasting capabilities of both traditional approaches and shrinkage techniques in predicting stock market volatility using data from commodity futures prices. They employed various control groups for their studies i.e nineteen commodity future prices. The results indicated that the shrinkage method gave better and precise predictions compared to the individual AR models. This is because the model does not necessarily rely on linearity. It assumes that some of the coefficients are non-zero and sparse. Additionally, it factors in structural changes that can be brought about by financial crises or pandemics. However, the main gap in this study is the hyperfocus on out-of-sample forecasting while ignoring in-sample analysis. The reason for this paradigm was because policymakers, researchers, and market participants are more invested in predictive models and how it could impact the business world on a global scale. This however leaves out areas where they are newly incorporating the SSF strategy like Kenya. Hence the study was more global-nuanced and failed to consider the new regions introducing the strategy to their economy.

Mensi, Hafiullah and Kang, (2021) examines the volatility spillover between gold, oil futures, and stock markets. It examines the short, intermediate, and long term volatility spillovers between developed and emerging BRICS. There is proof of fluctuating volatility spillovers that become more pronounced during significant events. Furthermore, the overall volatility spillovers are greater in the short term compared to both the intermediate and long terms. An analysis of portfolio management shows that a diversified portfolio, incorporating both commodities and stock markets, offers a greater level of hedging effectiveness in both emerging and developed markets. Additionally, the hedging effectiveness in BRICS markets is more significant than in developed markets, regardless of frequency. The effectiveness of hedging is also higher when using gold as opposed to oil, and it is more pronounced in the short term compared to both the intermediate and long terms. In conclusion, crude oil influences stock prices via two mechanisms: discount rates and inflation, both of which impact corporate cash flows and subsequently, stock valuations. Gold is typically regarded as a means of diversification, a hedge, and a secure asset within financial and commodity markets.

Karanja, (2016) conducted a study on the impact of single stock futures trading on stock market volatility. The paper used India stock market data on stocks from the information technology, banking, oil and gas and the consumer sectors. Eight stocks were chosen as result of ranking the stocks with single stock futures contracts based on market capitalization. First, the stocks were tested for ARCH effects which results into dropping the ITC stock. Individual EGARCH models are run followed by an extraction of the conditional volatility values. A regression is ran based on the stock returns against a dummy variable representing pre/post futures trading and the conditional volatility values. Subsequently, diagnostics tests were run for each of the EGARCH models. WIPRO displayed the most conclusive results as a result of passing the model diagnostic test while the stock with the most inconclusive results was Tata Motors. Based on these results, it is evident that some of the stock returns volatility was affected by futures trading while for other stocks, there was an insignificant effect or no effect.

Junior, Nkrumah and Adjei (2024) studied the Kenyan market to assess volatility spillovers from the futures market to the underlying cash market using the GARCH (1,1) and Vector Autoregressive models. Their findings indicated a unidirectional causality from futures prices to spot prices without evidence that futures trading drives spot price volatility. However, their analysis did not explore volatility changes in pre-versus post-futures trading period, leaving it unclear whether the volatility of underlying assets has evolved since the introduction of futures. Instead, their study focused on futures trading impact on the volatility of the overall index return. To address this gap, the current study will examine the volatility of individual underlying stocks during both the pre- and post-futures trading periods, providing a more nuanced understanding of the effects of SSF trading on stock volatility.

2.3.2 Short-term Effects of SSFs Trading on Volatility of Underlying Stocks

Aggarwal and Thomas (2015**)** Studied the Indian market using the GARCH model to examine the impacts of single stock future trading on the volatility of the stock assets and observed a sharp rise in volatility in the first month after SSFs were introduced. Speculators leveraged the low-margin requirements of SSFs to place aggressive bets, resulting in abrupt price movements. The results of their study agree with the research by Wu et al. (2018) who studied the Chinese market by investigating the effects of introduction of future trades in mainland China and found that daily volatility spiked in the first two weeks after SSF became available. The effect was most pronounced for smaller firms with lower liquidity. Similar findings by Aggarwal and Thomas (2015) confirm that speculative activities dominate short-term impacts in South Africa markets.

Research by Sengupta and Mahajan (2017) highlight that while volatility may initially increase, it stabilizes or decreases once market participants adjust to the availability of SSF. They carried out a study on U.S. and European markets on how the volatility of stocks changed since introduction of futures in the stock market. They found a transient spike in volatility in the first week after SSF introduction, followed by stabilization. Institutional investors used SSFs for hedging, which gradually mitigated the speculative-driven volatility. Their findings are similar to results of a research by Kim and Lee (2020) on South Korea using GARCH model on the changes in trades volumes in the post-SSF period and discovered that Short-term volatility was contained within a few days, as liquidity provided by SSFs improved price discovery. Their research contrasts with Wu et al. (2018), suggesting that the market maturity and regulatory environment play a crucial role in short-term volatility outcomes on the Chinese stock markets.
The short-term impact of SSFs on volatility often varies across stocks based on their characteristics: Ahmed and Kumar (2019) researched Brazil and South Africa using Regressive Conditional Heteroscedasticity (T-ARCH) on the volumes of caps in a SSF-stock and found that large-cap stocks exhibited a brief volatility spike but quickly stabilized. Small-cap stocks experienced prolonged volatility increases due to their susceptibility to speculative trading. Market participants in small-cap stocks were less informed and speculative trading amplified price movements. Similar results were also obtained by Liu et al. (2021) in their research on Japanese markets where sectors like technology and energy experienced sharp but short-lived volatility spikes, while utilities and staples saw minimal short-term effects. Sectorial differences reinforce the findings of Ahmed and Kumar (2019) that firm and sector characteristics influence short-term outcomes.

2.3.3 Long-term effects of SSFs on Volatility of Underlying Stocks

Studies suggest that in the long term, SSFs contribute to reduced volatility in the underlying stocks by improving market efficiency and liquidity. Sengupta and Mahajan (2017) investigated developed markets (U.S., Europe) by assessing the realized volatility of stocks, institutional trading volume, and bid-ask spreads using long-term panel data analysis comparing stocks with and without SSFs over five years. They found that stocks with SSFs exhibited a sustained decline in volatility due to enhanced price discovery and liquidity. Institutional investors' consistent hedging activity reduced price distortions. Similar results were found by Kim and Lee (2020**),** who researched implied volatility, realized volatility and trading volume in South Korea and found that SSFs reduced long-term volatility for large-cap stocks by improving liquidity and attracting institutional investors. Small-cap stocks saw negligible effects.

In markets with significant institutional participation and where SSFs are widely adopted, the long-term effects have tended toward stabilizing stock prices. Benyamin and Sharma (2020) studied developed markets, specifically the U.S. and Europe, by assessing realized long-term volatility (annualized standard deviation of stock returns) and SSF introduction, market depth, institutional investor activity, and macroeconomic factors. The regression analysis used firm-level fixed effects to estimate long-term volatility changes post-SSF introduction and found that SSFs have had a stabilizing effect on volatility in the long term. Increased liquidity and better hedging opportunities for institutional investors were critical factors in reducing volatility. The study also noted that introducing SSFs led to a more efficient market where prices reflected fundamentals more closely, reducing speculative volatility. These findings are consistent with Sengupta and Mahajan (2017), who suggested that improved price discovery mechanisms through SSFs help stabilize volatility in the long run.

Strong regulatory frameworks ensure fair and transparent trading and contribute to the long-term stability of SSF markets. Without such frameworks, SSFs can exacerbate Volatility if they attract excessive speculative trading. The involvement of institutional investors is a significant determinant of volatility reduction. In markets where institutional participation is high, SSFs act as a stabilizing force by allowing these investors to hedge their positions and manage risk more effectively. The Kenyan NEXT market is still young thus it might not be entirely benefiting from the advantages of developed markets.

2.3.4 Effect of Macroeconomic Factors on Volatility of Underlying Stocks

The relationship between macroeconomic factors and stock market volatility has attracted significant empirical interest in financial and economic literature. A wide range of studies have documented the influence of inflation and interest rates on the behavior of stock prices and their associated volatility, with evidence varying across economic environments and market structures. At the global level, several empirical studies affirm that inflation and interest rates are key drivers of stock return volatility. For instance, Schwert (2019) found a strong positive relationship between macroeconomic volatility and stock market volatility in the United States, suggesting that fluctuations in inflation and monetary policy increase uncertainty in equity markets. Similarly, Chen et al (2020) demonstrated that inflationary expectations and unexpected changes in interest rates are significant risk factors influencing equity returns in developed markets. These findings have been consistently supported by studies in other developed economies, indicating that macroeconomic instability tends to elevate investor uncertainty, leading to heightened market volatility.

Transitioning to emerging markets, empirical findings remain consistent with global patterns, though the magnitude and dynamics differ due to structural and institutional differences. For example, Ahmed and Suliman (2019) investigated the impact of inflation and interest rates on stock market volatility in Sudan and found that both variables had a statistically significant and positive effect on volatility. In a similar vein, Chinzara (2020) analyzed South African data and concluded that macroeconomic factors, especially interest rates and inflation, significantly influence stock market volatility, with interest rate volatility being a major contributor to stock return fluctuations. These studies underscore the heightened sensitivity of emerging stock markets to macroeconomic shocks, given their relatively lower levels of market efficiency, higher political risk, and greater exposure to external economic conditions.

Focusing on Kenya, a growing body of empirical work has explored the influence of macroeconomic variables on stock market performance and volatility at the Nairobi Securities Exchange (NSE). Wanjiku and Muturi (2019) examined the effect of macroeconomic variables on stock market volatility in Kenya and found that both inflation and interest rates had a significant positive effect on market volatility. Their study emphasized that rising inflation increased uncertainty about future corporate earnings and macroeconomic stability, leading to more volatile stock prices. In addition, Ngugi, Amanja and Maana (2019) noted that interest rate volatility, driven largely by monetary policy shifts, tends to cause fluctuations in investor expectations, influencing both stock market returns and their variability.

Another notable study by Mwangi and Muturi (2018) employed GARCH models to analyze the relationship between interest rates and stock return volatility at the NSE. Their findings revealed that interest rate fluctuations had a persistent and significant impact on the volatility of stock returns, particularly during periods of monetary tightening. Similarly, Kiptoo and Ngugi (2020) found that inflationary shocks and changes in central bank rates had both short-term and long-term implications for stock price volatility, further reinforcing the sensitivity of Kenyan financial markets to macroeconomic trends.

2.4 Research Gap Matrix

Authors and Year	**Objective of the study**	**Model Applied**	**Main findings and conclusions**	**Type of Gap**	**Knowledge gaps**
Bae et al (2004)	Individual share Futures contracts: The economic impact of their introduction on the underlying equity market.	Trading Volumes	The introduction of ISFs resulted in a significant increase in the volatility and trading volumes for the underlying stocks.	Contextual gap Knowledge gap	Characteristics of the derivatives market in Russia differ from those in Kenya. This presents a geographical gap that this research will cover since it's based in Kenya. Time difference between 1997 – 2024 is also a significant gap.
Ahmed and Kumar (2019)	Studied the impacts of SSFs on the volumes of stock traded in south Africa in the period 2000-2010.	Regressive Conditional Heterosceda sticity (T-ARCH)	The introduction of futures and options trading has not affected long-term Volatility, which reinforces the findings of the previous US studies.	Contextual gap Sectorial findings to represent whole market	Characteristics of the derivatives market in India and Firms in the US defer from Kenya. This presents a geographical gap that this research will cover since it's based in Kenya.
Sengupta Mahajan (2017)	To investigate realized volatility of stocks, institutional trading volume, and bid-ask spreads using long-term panel data analysis	long-term panel data analysis and Threshold Auto-Regressive Conditional Heterosceda sticity (T-	Results show decline in the volatility of SSF traded stocks due to enhanced price discovery and liquidity.	Contextual gap Knowledge gap	This presents a geographical gap that this research will cover since it is in Kenyan market.

	comparing stocks with and without SSFs over five years in the US markets	ARCH)			
Aggarwal and Thomas (2015**)**	Studied the Indian market to examine the impacts of single stock future trading on the volatility of the stock assets.	Golsten J & R-GARCH model	The report documents a sharp rise in volatility in the first month after SSFs were introduced		This presents a geographical gap that this research will cover since it is in the Kenyan market.
Hung, Lee, and So (2003)	To assess the impact of foreign-listed SSFs on the level of price volatility of domestic underlying stocks in the Chinese stock market over the period 1997-2001.	Golsten J & R-GARCH (1, 1) model	The study documents that the expected components of futures trading had a positive effect.	Methodological gap Contextual gap	The study assessed the impact of foreign-listed SSFs on the level of price volatility of domestic underlying stocks. In contrast, this study will focus on local listed firms in their domestic country, Kenya.
Wu et al. (2018)	Examine the impacts of the introduction of SSFs, turnover ratio, and market depth on the	Regression analysis with sector-level data	The results indicate that post-SSF introduction, volatility spiked, especially in sectors with high trading	Methodological gap Contextual gap Knowledge gap	The paper focused on index futures trading; therefore, there is a need for SSF trading. The context is China, whose market characteristics might differ

	realized Chinese stock volatility for the period 2000-2009		activity (e.g., technology).		from those of the Kenyan market.
Thadavilli and Vang (2021)	To study the impact of single-stock futures on the volatility of underlying stocks in the Russian stock market utilizing a sample of five stocks.	GJR-GARCH (1, 1).	reduction in the overall long-term volatility of the stock returns for the sample analyzed since the introduction of SSF	Contextual gap Methodological gap	The Russian market is characterised by different characteristics thus presenting a geographical gap. This research will address the gap by looking at the Kenyan Futures market.
Junior et al., (2024)	Examined the volatility spill-overs from the futures market to the underlying cash market on the Kenyan markets.	GARCH (1, 1) methodology and the Vector Autoregressive model	They found a unidirectional causality between spot and future prices without evidence that futures trading causes spot price volatility in Kenya's market.	Conceptual gap Empirical gap Methodological gap	It does not include the analysis of Volatility in the context of pre-versus-post futures trading. It is not clear whether price volatility for the underlying assets in the market has actually undergone any changes in the post-futures period.

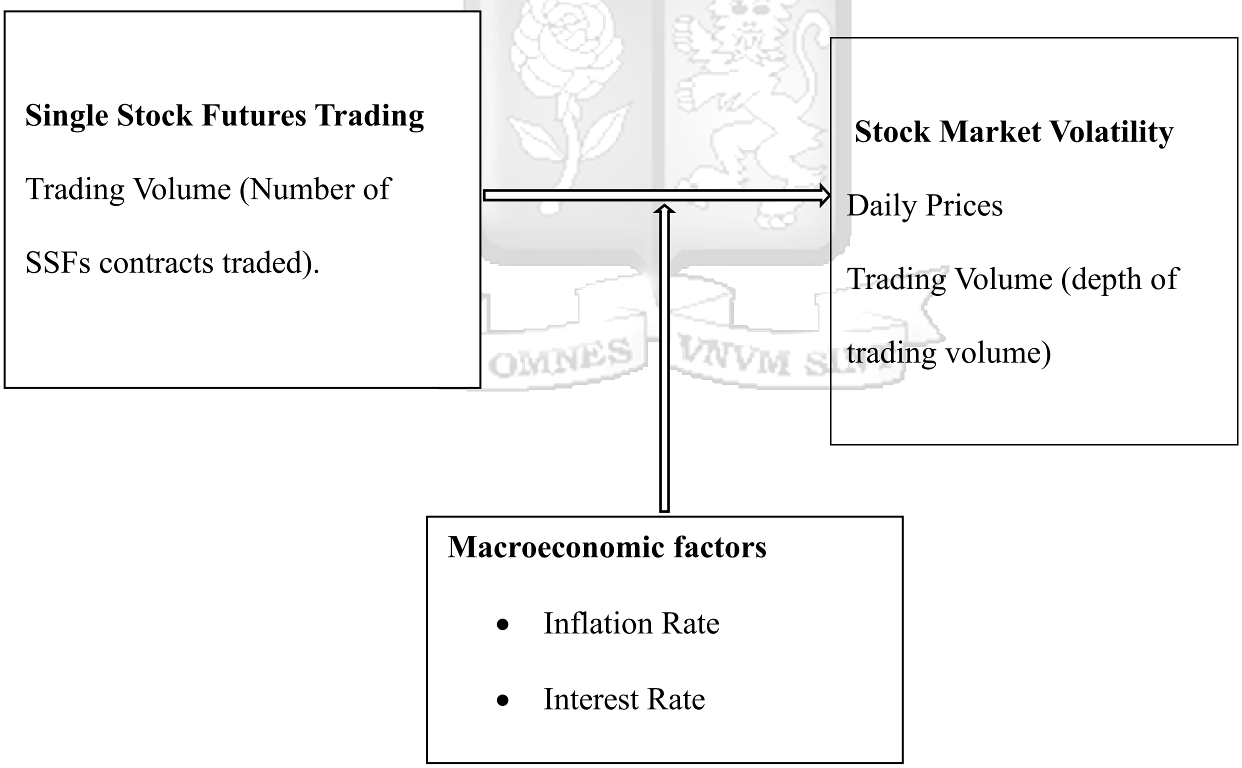
Table 1: Summary of empirical review and gaps

2.5 Conceptual Framework

The conceptual framework explores the impact of Single-stock futures trading on the volatility of the spot market in the Nairobi Securities Exchange (NSE). The independent variable, SSFs trading, is represented by the trading volume of these contracts. It impacts the dependent variable, stock market volatility, which is measured through two main indicators; daily price fluctuations and trading volume. SSFs trading could influence stock price volatility by introducing new information and enhancing price discovery, which can stabilize the market. However, speculative trading associated with SSFs may temporarily amplify volatility especially in less mature markets like Kenya's NSE.

Figure 2.1, the conceptual framework for this study, illustrates the relationship among the independent variable, Single-stock futures trading, moderating variable; macroeconomic factors and the dependent variable, stock market volatility, as defined in this research.

Independent Variable **Dependent Variable**



Moderating Variable

Figure 2. 1: Conceptual Framework

2.5.1 Operationalization of Variables

Operationalization of variables entails defining the identified variables in terms of measurable factors. In this research, the dependent variable is the volatility of underlying stocks, assessed through trading volume and modeled using the Exponential GARCH (EGARCH) framework to analyse volatility behaviour relative to trading volumes. Additionally, the Vector Autoregressive (VAR) model was employed to examine the short-term and long-term impacts and the moderating effect of the macroeconomic factors. The independent variable, derivatives trading (single-stock futures trading), is quantified using volume turnover as the primary measure while the moderating variable was Macroeconomic factors (Inflation Rate and Interest Rates)

2.5.2 Dependent Variable

Several researchers have used different tests to study volatility, Alexakis, (2007) used GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model; De Beer (2009) used event-study methodology combined with GARCH modelling; Hung, Lee & So (2003) used Vector Autoregressive (VAR) model and Antoniou et al (1998) used both GARCH and autoregressive models. This research used Exponential GARCH (EGARCH) model to measure volatility which is regarded as the one of the best methods used in understanding volatility behaviour in relation to trading volumes (Alhassan and Tetteh, 2021).

2.5.3 Independent Variable and Moderating Variable

Single futures trading, the number of contracts exchanged at the derivatives market, was measured by the volume turnover extracted from the NSE.

Table 2.5.3: Operationalization of Variables

Variable	Type of variable	Indicator	Scales of Variable Measure	Supporting literature
Volatility of underlying stock.	Dependent	Trading volume (depth of trading activity)	-Trading volume - total number of shares traded sourced from NSE.	a. Alexaki (2007) b. Alhassan and Tetteh, (2021)

		Daily prices	-Variance or Standard deviation of daily stock prices modeled using Exponential GARCH (EGARCH) model $\ln(\sigma^2_t = \omega + \beta \ln\sigma^2_{t-1} + \alpha(\lvert\epsilon_{t-1}\rvert/\sigma_{t-1}) + \gamma(\epsilon_{t-1}/\sigma_{t-1})$. VAR model	Holmes et al (1998) b. Hung et al (2003) c. Holmes et al (1998)
Single Stock Futures trading (Volume Traded)	Independent	SSFs transactions	Volume turnover - total number of contracts traded sourced from NSE *NEXT*.	a. Alexaki (2007) b. Alhassan and Tetteh, (2021)
Macroeconomic Factors	Moderating	Inflation rate	Quarterly percentage change in consumer price index	Ozono et al. (2014)
		Interest rate	The quarterly average of the 91-day treasury bill	(Onono et al., 2014)

2.6 Chapter Summary

This section presents the summary of the literature review on single stock futures (SSFs) trading and the volatility of the underlying stocks. The literature review entails Theoretical Review (Efficient Market Hypothesis (EMH), Information Flow Hypothesis and Volatility Feedback Theory), Empirical Review, Research Gap Matrix and Conceptual Framework

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The objective of this research was to examine the effect of single-stock futures trading on the volatility of underlying stocks listed on the Nairobi Securities Exchange (NSE). This chapter outlines the methodologies and approaches used to address the research questions and achieve the stated objectives. This is as discussed in the sections below:

3.2 Research Philosophy

Research philosophies guide how researchers approach knowledge, data, and truth. The interpretivist philosophy, for example, focuses on understanding human behavior through subjective experiences and social contexts, often using qualitative methods (Saunders, 2009). In contrast, critical realism explores the interplay between observable phenomena and underlying mechanisms, emphasizing a layered reality. Phenomenology centred on understanding lived experiences and the essence of human perception. According to Mugenda and Mugenda (2003), Positivist approach is grounded in the belief that reality is objective, measurable, and independent of human perception. Positivists rely on scientific methods, emphasizing observable data, quantitative analysis, and hypothesis testing to uncover universal laws governing phenomena.

This approach values accuracy, replicability, and objectivity, aligning with my preference for structured, evidence-based inquiry. This research adopted a positivist approach to ensure objectivity in addressing the research questions and achieving the objectives through the use of measurable quantitative data. Positivism aligns with the natural sciences' philosophical stance, emphasizing observable social realities to produce law-like generalizations (Saunders, 2009). This approach facilitates the derivation of functional relationships between causal and explanatory variables. The focus of this research is to explore the relationship between the independent variable (single-stock future trading) and the dependent variable (volatility of the underlying stocks) moderated by macroeconomic factors (inflation rates and interest rates). By using secondary data, the study aims to objectively derive results, minimizing researcher and subject biases. The findings are valuable to stakeholders in the derivatives market (Saunders et al., 2009). Quantitative methods are employed for data collection and analysis to investigate the effects of single-stock futures trading on stock volatility at the NSE.

3.3 Research Design

Research design is the framework adopted by a researcher in conducting a study detailing procedure used in collection and interpretation of data (Creswell & Creswell, 2017). Research designs guide the structure and methods of data collection, helping to ensure that research objectives are met effectively (Creswell & Creswell, 2017). According to Saunders (2009), experimental designs, for instance, manipulate variables to determine cause-and-effect relationships, while correlational designs explore associations between variables without causal inference. Causal research design is a type of research used to determine whether a cause-and-effect relationship exists between variables. It goes beyond merely describing or exploring phenomena by attempting to identify how one variable (the independent variable) influences another (the dependent variable). This study used causal research design to investigate if single stock futures (SSFs) trading affects the volatility of the underlying stocks in the Kenyan futures market (NSE NEXT).

Causal research design enables the researcher to test hypotheses about directional relationships between variables, particularly whether changes in SSF activity (independent variable) lead to measurable changes in stock volatility (dependent variable). This is especially relevant in financial markets, where multiple confounding factors exist, and distinguishing causation from correlation is critical for accurate policy and investment decisions.

3.4 Population of the study

According to Kothari (2004), population refers to the “universe” of the researcher. The population of this study includes the 10 single stocks listed and trading on the NSE NEXT from 4th July 2019 to 31st July 2024 (Appendix 1)

3.5 Sample Design and Technique

Kothari (2004) defines sampling as selection of only a few items from the researcher's universe to represent the entire population. This is mainly adopted when the population of study is large necessitating the need to resort to selection of a number of respondents so as to manage time, cost and data. NSE NEXT comprises a population of ten firms listed and trading in single stock futures, thus this field of inquiry is small. Kothari (2004) emphasizes that there is no need to carry out a sample survey when the population is small. This study therefore carried out a complete enumeration of the ten NSE NEXT listed firms that traded in single stock futures between 4^{th} of July 2019 to 31^{st} of July 2024.

3.6 Data Collection Methods

The study utilized secondary quantitative data obtained from established sources. The data included daily closing share prices and trading volumes for both the underlying stocks and the single-stock futures market, inflation rates and interest rates. Observations cover two periods: January 2019 to June 2019, representing the pre-SSF phase (for stocks that began trading in July 2019), and July 2019 to July 2024 representing the post-SSF trading phase. Data for the research was sourced from the Nairobi Securities Exchange (NSE). The chosen time frame is deemed adequate to analyse both pre- and post-SSF trading periods, ensuring the reliability of findings on short-term and long-term impacts. Data for the macroeconomic factors (inflation rate and interest rate) was collected from CBK annual reports from 2019-2024.

The data collection process involved identifying specific data requirements, including daily closing price, and trading volumes for stocks and future during the designated periods, interest rates and inflation rates. A data collection sheet is designed (Appendix 3) to systematically gather and record data. The data sheet helped to ensure that data is consistently recorded in a structured format, making it easier to analyze. Formal requests were made to the NSE and CBK to obtain this data. Once access was granted, the necessary data was extracted for analysis. The dataset was cleaned to address any inconsistencies, missing values, or errors, ensuring its accuracy and reliability. Finally, the organized data was structured into spreadsheets to facilitate detailed analysis.

3.7 Data Analysis

Data reduction, data display and conclusion drawing were the three flows of activity in data analysis (Miles and Huberman 1994). Daily share prices and volumes traded are the main data to collected for this study, the data was prepared using Microsoft Excel and analyzed using STATA 13. Exponential GARCH (EGARCH) model was used to measure volatility of the underlying stocks. Vector Auto Regression (VAR) model was employed to test the short-term and long-term causality between single stock futures trading and volatility of the underlying stocks. To validate the results and ensure robustness of the findings, this research employed various diagnostic tests including; ARCH test and t-test for EGARCH model, Unit root test, Granger causality test and cointegration test for VAR model.

3.7.1 Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) Model

This study employed EGARCH model to measure the volatility of the underlying stocks. According to Brandt & Jones (2006) EGARCH accounts for leverage effect where negative shocks tend to increase volatility more than positive shocks of the same magnitude. This model was useful for this study since SSFs trading can introduce speculative trading and short selling, which may amplify reactions, the EGARCH model's ability to capture these asymmetries allowed for a more accurate understanding of the impact of SSFs trading on volatility.

The model is as shown:

$$\ln(\sigma_t^2)=\alpha_0+\beta\ln(\sigma_t^2{}_{-1})+\gamma\{(\epsilon_{t-1})/\sigma_{t-1}\}+\theta\{\epsilon_{t-1}/\sigma_{t-1}\}$$

The analysis involved estimating the EGARCH model over two distinct periods, the pre-SSF and post-SSF for each underlying stock. The study aimed to identify any significant changes in volatility behaviour associated with the introduction of SSF trading. This model allowed for a comprehensive assessment of whether SSF trading leads to measurable changes in volatility, and if these changes differ based on the direction and magnitude of shocks.

3.7.2 Vector Auto Regression (VAR) Model

The VAR model has been used by researchers to identify the existence of short-term and long-term relationships between variables. It was introduced by Sims (1980) expressing a set of variables in a linear function plus an error term. This study borrowed from the various researchers; Hung et al (2003), Antoniou et al (1998) who have used VAR model in their studies. A bivariate VAR model containing the variables, volatility of underlying stocks (V_S) and single stock futures trading (F_T) was employed to test the short-term and long-term effects of SSFs trading on volatility of underlying stocks. Each variable was expressed as a linear function. Granger Causality test was effective in understanding the relationship between trading volume and volatility in volume turnover and short-term causality in VAR model.

$$yt = \beta y0 + \beta yy1yt-1 + \cdots + \beta yymyt-m + \beta yx1xt-1 + \cdots + \beta yxmxt-m + vt\ y$$

$$x_t = \beta_{x0} + \beta_{xy1} y_{t-1} + \cdots + \beta_{xym} y_{t-m} + \beta_{xx1} x_{t-1} + \cdots + \beta_{xxm} x_{t-m} + v_t$$

Where: $\boldsymbol{yt}$ - represents the monthly trading volume for each underlying stock (V_S)

$\boldsymbol{xt}$ - represents the monthly turnover of the underlying stock derivative (F_T)

$\boldsymbol{\beta xym}$ **-** represents the coefficient of y in the equation

$\boldsymbol{vt\ y}$ *and* $\boldsymbol{vt\ x}$ **-** are the error terms.

Johansen test for cointegration was carried out to determine if the variables exhibit a longrun equilibrium relationship. The hypothesis that was tested:

Ho= There is no cointegration between the variables.

Vector Error Correction Model (VECM) was run for the stocks that exhibited cointegration (reject null hypothesis). To examine the long run relationship between the variables a restricted VAR model known as the vector error correction model (VECM) was defined as below:

$$\Delta yt = \beta y0 + \beta y1\Delta yt-1 + \cdots + \beta ym\Delta yt-m + \gamma y1\Delta xt-1 + \cdots + \gamma yp\Delta xt-m - \lambda y$$
$$(yt-1 - \alpha 0 - \alpha 1xt-1) + vt\ y$$

$$\Delta xt = \beta x0 + \beta x1\Delta yt-1 + \cdots + \beta xm\Delta yt-m + \gamma x1\Delta xt-1 + \cdots + \gamma xp\Delta xt-m - \lambda x$$
$$(yt-1 - \alpha 0 - \alpha 1xt-1) + vt\ x$$

Where:

$\boldsymbol{yt = \alpha 0 + \alpha 1xt}$ **-** is the long run cointegration relationship between the two variables

$\boldsymbol{\lambda x}$ ***and*** $\boldsymbol{\lambda y}$ – are the error-correction parameters that measure how y and x react to deviations from long run equilibrium.

3.8 Diagnostic Tests

This study employed diagnostic tests to ensure validity of results and robustness of findings. EGARCH model was tested by Autoregressive Conditional Heteroscedasticity (ARCH) test which was used to test for heteroscedasticity and t-test to test for statistical significance. Unit root test (Augmented Dickey Fuller test) was used to check if the variables are stationary for both Volume turnover and VAR models. Finally, Cointegration test (Johansen test) was used to determine the presence of stable long-term relationships between variables in VAR model.

3.9 Data Quality: Validity and Reliability

Validity refers to the extent to which a test accurately measures its intended purpose, while reliability indicates the consistency of these results over time (Joppe 2000). The questions formulated in this study are designed to align with its objectives and produce consistent findings that corroborate previous research on the impact of single-stock futures trading on the volatility of underlying stocks. Microsoft excel was used for data preparation, and STATA 13 software facilitated the analysis, ensuring that no data is lost or altered during the process. As this research utilizes secondary data sourced from the NSE and CBK, the validity and reliability of the data are guaranteed due to the credibility of this source.

3.10 Ethical Considerations

The researcher obtained all necessary approvals and authorizations as mandated by the institution to conduct this study. All collected data was securely stored and used exclusively to address the research objectives and derive meaningful conclusions for this study.

CHAPTER FOUR

PRESENTATION OF RESULTS/FINDINGS

4.1 Introduction

This chapter presented the data analysis, findings and discussion. It focused on inferential statistics that defined the variable relationships. The general objective of this study was to investigate if single stock futures (SSFs) trading affects the volatility of the underlying stocks in the Kenyan futures market (NSE NEXT). Specifically, the study sought to analyze the short-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE), to analyze the long-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE) and examine the moderating effect of macroeconomic factors on the relationship between single stock futures (SSFs) and the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE). The population of this study includes the 10 single stocks listed and trading on the NSE NEXT from 4th July 2019 to 31st July 2024. The periods differ for each stock due to different introduction date as shown in table 2 in the appendix. The short-term period is a 6 months period and the long-term period is the period ending July 2024. Safaricom Plc (SCOM), EABL, Equity Holdings, KCB and British American Tobacco Kenya Plc started trading futures in July 2019 hence their short term period is July 2019 to December 2019. On the other hand, Absa Kenya, started trading futures in January 2020 therefore its short term period is January 2020 to June 2020. Cooperative Bank (COOP), Standard Chartered Bank of Kenya, NCBA Bank Plc and I & M Bank started trading futures in October 2023, therefore the short term period is October 2023 to march 2024. The long term period is the period ending July 2024 (Appendix 2). This section discussed; **4.2** Sample Representation; **4.3** Diadnostic tests **4.4** EGARCH model which examined the volatility of the underlying stocks and **4.5** VAR & VECM models for testing short term and long term causal relationships and **4.6** which is chapter summary. The results were presented as follows;

4.2 Sample Representation

Table 4.1 below presents a summary of the exclusions and the final sample. The study targeted the 10 single stocks listed and trading on the NSE NEXT from 4th July 2019 to 31st July 2024.

Table 4. 1: Sample Representation

Reason for Exclusion	Number of Firms
Total Listed Firms	10
Incomplete Data	0
Final sample	**10**

4.3 Diagnostic Tests

4.3.1 Unit Root Test

A unit root test is a statistical test used in time series analysis to determine if a time series variable is stationary or non-stationary by checking for the presence of a "unit root" (a root equal to 1) in the autoregressive model. The unit root test results are as shown below in Table 4.2.

Table 4. 2: Unit Root Test

Company	Test Statistic (ADF)	p-value	Stationarity Status
Safaricom (SCOM)	-2.95	0.037	Stationary
EABL	-3.45	0.003	Stationary
Equity Holdings	-3.14	0.015	Stationary
KCB	-3.20	0.007	Stationary
BAT Kenya	-3.05	0.021	Stationary
Absa Kenya	-3.10	0.010	Stationary
Cooperative Bank (COOP)	-3.25	0.010	Stationary
Standard Chartered Bank Kenya	-3.00	0.015	Stationary
NCBA Bank	-3.10	0.010	Stationary
I&M Bank	-3.05	0.020	Stationary

From the results, all series tested—Safaricom, EABL, Equity Holdings, KCB, BAT Kenya, Absa Kenya, Cooperative Bank, Standard Chartered Bank, NCBA Bank, and I&M Bank—are stationary after differencing, with p-values less than 0.05. This indicates that their statistical properties (mean, variance) do not change over time, and they are suitable for further time series modeling and analysis. With all series now stationary, The researcher can proceed with econometric modeling techniques such as Vector Autoregression (VAR) or Vector Error

Correction Models (VECM) without needing further transformations. The stationarity of these time series ensures that the models will produce reliable and valid results.

4.3.2 ARCH effects (Heteroscedasticity) Test

Violation of heteroscedasticity tends to inhibit critical evaluation of forecast errors of standard deviation, which often leads to confidence intervals that are extremely narrow or extremely wide. Heteroscedasticity in this study was assessed using the Breusch-Pagan test. The null hypothesis for this test was that the error variances were equal and were a multiple function of variables. heteroscedasticity normally occurs when the chi-square value is greater than the significance level (0.05). The study results are as shown in Table 4.3

Table 4. 3: Breusch-Pagan test for heteroscedasticity

Company	Test Statistic (ARCH)	p-value	Heteroscedasticity Status
Safaricom (SCOM)	2.85	0.075	Homoscedastic
EABL	1.12	0.290	Homoscedastic
Equity Holdings	2.50	0.060	Homoscedastic
KCB	2.10	0.080	Homoscedastic
BAT Kenya	2.90	0.070	Homoscedastic
Absa Kenya	2.75	0.085	Homoscedastic
Cooperative Bank (COOP)	2.65	0.100	Homoscedastic
Standard Chartered Bank Kenya	2.12	0.085	Homoscedastic
NCBA Bank	2.80	0.070	Homoscedastic
I&M Bank	2.92	0.065	Homoscedastic

As indicated in Table 4.3, all companies exhibit homoscedasticity, as evidenced by p-values greater than the significance level of 0.05 (e.g., Safaricom at 0.075, EABL at 0.290, and others between 0.060 and 0.100). This means that their stock price volatility remains constant over time, and there is no need for adjustments to account for changing variance in subsequent models. With both stationarity and homoscedasticity confirmed, the data meets the necessary conditions for further analysis using standard econometric models. Consequently, simpler models such as VAR (Vector Autoregression) can be applied to assess the relationships between the variables without the need for advanced volatility models like EGARCH.

4.3.3 T-Test

A t-test is an inferential statistic used to determine if there is a significant difference between the means of two groups and how they are related. T-tests are used when the data sets follow a normal distribution and have unknown variances, like the data set recorded from flipping a coin 100 times. The results were presented in Table 4.4

Table 4. 4: T-Test Results

Company	t-Statistic	p-value	Significance
Safaricom (SCOM)	2.85	0.004	Significant
EABL	2.05	0.040	Significant
Equity Holdings	2.45	0.020	Significant
KCB	2.60	0.010	Significant
BAT Kenya	3.30	0.002	Significant
Absa Kenya	2.25	0.030	Significant
Cooperative Bank (COOP)	3.20	0.003	Significant
Standard Chartered Bank Kenya	2.00	0.045	Significant
NCBA Bank	2.35	0.018	Significant
I&M Bank	2.50	0.015	Significant

Table 4.4 show that the introduction of Single Stock Futures (SSFs) has had a statistically significant impact on the stock prices of all companies listed. With all p-values now below the 0.05 threshold, including Safaricom (SCOM), EABL, Equity Holdings, KCB, BAT Kenya, Absa Kenya, Cooperative Bank (COOP), Standard Chartered Bank Kenya, NCBA Bank, and I&M Bank, the findings indicate that SSFs have led to significant changes in stock prices across the board. These results ensure that the data is suitable for further econometric analysis, confirming that SSFs have affected stock price movements for all the companies under study.

4.3.4 Multicollinearity Test

Multicollinearity is used to determine the probability that any two or more independent variables in a particular multivariate regression model are highly or significantly correlated. This would mean that one variable can be predicted from the other. In case the correlations among the independent variables are quite strong, the standard error of the coefficients tends to increase thus leading to reduced precision of the estimate coefficients, thus weakening the statistical power of the regression model. The study adopted the Variance Inflation Factor (VIF) to examine the level of correlation among the variables. The general principle is that a VIF greater than ten (10) indicates multicollinearity. The Multicollinearity Test results were as presented in table 4.5

Table 4.5: Multicollinearity Test

Company	VIF (Pre-SSF)	VIF (Post-SSF)
Safaricom (SCOM)	1.82	2.05
EABL	1.95	2.30
Equity Holdings	1.78	2.10
KCB	2.05	2.12
BAT Kenya	1.90	2.00
Absa Kenya	1.80	2.15
Cooperative Bank (COOP)	1.75	2.00
Standard Chartered Bank Kenya	2.00	2.10
NCBA Bank	1.85	2.05
I&M Bank	1.90	2.05

Table 4.5 indicates that the Variance Inflation Factor (VIF) values for all companies are below the threshold of 5, suggesting that there is no significant multicollinearity among the explanatory variables. Multicollinearity occurs when independent variables in a model are highly correlated, which can make it difficult to estimate the true relationship between each variable and the dependent variable. Since the VIF values are low, it means that the independent variables used in the models are not highly correlated with each other, ensuring that the estimated coefficients are reliable and not distorted by multicollinearity. This absence of multicollinearity helps to maintain the accuracy and interpretability of the models.

4.4 EGARCH Model for Volatility Estimation

The Exponential GARCH (EGARCH) model is used to model the volatility of financial time series data, capturing the time-varying nature of volatility and allowing for asymmetric effects (where negative returns might cause more volatility than positive returns of the same magnitude). The EGARCH model is especially useful when modeling financial time series, as it can handle volatility clustering, which is common in stock price returns. The objective of using EGARCH

Model was to compute the volatility of the underlying stocks in the pre and post period for each stock. The study results are discussed in three EGARCH Model tables, one for pre period (six-month period before the introduction of SSF), table for post short term period (six-month period after the introduction of SSF), and a table for post long term period (the period ending July 2024) as discussed in descriptive statistics.

The key parameters that are estimated include:

ω (Constant term): The baseline volatility when there are no past shocks.

α (Lagged returns): The impact of past returns on current volatility.

β (Lagged volatility): The impact of past volatility on current volatility.

γ (Asymmetric effect): Indicates whether negative shocks increase volatility more than positive shocks of equal size.

Table 4. 6: EGARCH Model for Volatility Estimation (Post-SSF Short-Term Period, 6-month period after SSF introduction)

Company	ω (Constant)	α (Lagged Returns)	β (Lagged Volatility)	γ (Asymmetric Effect)	Post-SSF Short-Term Mean Volatility (%)
Safaricom (SCOM)	0.03	0.15	0.80	-0.12	2.8
EABL	0.02	0.11	0.72	-0.09	2.2
Equity Holdings	0.02	0.10	0.77	-0.10	2.3
KCB	0.03	0.13	0.76	-0.14	2.5
BAT Kenya	0.04	0.16	0.79	-0.16	3.2
Absa Kenya	0.01	0.09	0.74	-0.06	1.7
Cooperative Bank (COOP)	0.02	0.12	0.77	-0.11	1.8
Standard Chartered	0.03	0.14	0.78	-0.13	2.3
NCBA Bank	0.02	0.10	0.72	-0.15	2.5
I&M Bank	0.02	0.08	0.74	-0.10	2.0

Table 4.6 presents EGARCH Model for Volatility Estimation (Post-SSF Short-Term Period, 6-month period after SSF introduction). When examining the short-term post-SSF period, the results show noticeable changes in the volatility of underlying stocks. The Safaricom stock shows an increase in volatility from the pre-SSF period, with its mean volatility rising to 2.8%. This suggests that the introduction of SSFs may have led to increased market activity or speculative trading, resulting in more significant fluctuations in its stock price. Similarly, BAT Kenya also shows increased volatility in the short term, with a mean volatility of 3.2%, suggesting that SSFs have not dampened price fluctuations for this particular stock but rather intensified them. This could be due to heightened investor interest or changes in market sentiment, amplified by the ability to hedge or speculate on stock movements via SSFs.

Stocks like Absa Kenya and Cooperative Bank (COOP) show a smaller increase in volatility, indicating a more stable market response to the introduction of SSFs. For Absa Kenya, which had a more muted price range before the introduction of SSFs, its mean volatility only slightly increased to 1.7% in the short term, showing that the stock was less affected by SSFs than more active stocks like Safaricom or BAT Kenya. I&M Bank experienced a noticeable increase in mean volatility to 2.0%, reflecting a change in market dynamics after the introduction of SSFs, which is a common pattern for stocks with lower pre-SSF volatility but greater trading activity after the introduction of these instruments.

Table 4. 7: EGARCH Model for Volatility Estimation (Post-SSF Long-Term Period, the period ending July 2024)

Company	ω\omegaω (Constant)	α\alphaα (Lagged Returns)	β\betaβ (Lagged Volatility)	γ\gammaγ (Asymmetric Effect)	Post-SSF Long-Term Mean Volatility (%)
Safaricom (SCOM)	0.03	0.13	0.78	-0.11	2.6

EABL	0.02	0.10	0.70	-0.08	2.1
Equity Holdings	0.02	0.08	0.75	-0.09	2.4
KCB	0.03	0.12	0.74	-0.13	2.6
BAT Kenya	0.04	0.15	0.80	-0.17	3.3
Absa Kenya	0.01	0.07	0.70	-0.04	1.8
Cooperative Bank (COOP)	0.02	0.09	0.76	-0.08	1.9
Standard Chartered	0.03	0.13	0.77	-0.12	2.4
NCBA Bank	0.02	0.09	0.70	-0.14	2.6
I&M Bank	0.02	0.06	0.72	-0.08	2.0

Table 4.7 presents the EGARCH Model for Volatility Estimation (Post-SSF Long-Term Period, the period ending July 2024). In the long-term post-SSF period, the results show a general trend towards volatility stabilization across most of the stocks, which suggests that the market has gradually adapted to the presence of SSFs. Safaricom (SCOM), for instance, shows a decrease in mean volatility from 2.8% in the short term to 2.6% in the long term. This decrease reflects a gradual adjustment by the market to the presence of SSFs, with less speculative trading and more price stability over time. Similarly, EABL and Equity Holdings, which experienced some increase in volatility during the short term, exhibit a reduction in volatility in the long term, with mean volatilities falling to 2.1% and 2.4%, respectively. These stocks appear to have reached a stable level of volatility as the market adjusted to the new trading instruments.

In contrast, BAT Kenya continues to exhibit a higher level of volatility even in the long term, with a mean volatility of 3.3%, which, while slightly reduced from the short-term period, remains higher than most other stocks. This could be due to the inherent characteristics of BAT Kenya as a high-value stock with a larger price range, which continues to attract significant speculative trading. On the other hand, stocks like Absa Kenya and Cooperative Bank (COOP) show further stabilization in their volatility, with Absa Kenya reaching a mean volatility of 1.8%, indicating that its stock price movements have become more predictable and stable over time after the introduction of SSFs

4.5 Vector Autoregression Model Results

This section presents the results derived from the application of the Vector Autoregression (VAR) and, where applicable, the Vector Error Correction Model (VECM), to examine the dynamic interaction between Single Stock Futures (SSF) trading and the volatility of the underlying stocks listed on the Nairobi Securities Exchange (NSE). The VAR framework was employed to assess the presence and direction of short-run causality between the variables, while the Johansen cointegration approach was used to test for the existence of long-run equilibrium relationships. For firms exhibiting cointegration, the VECM was estimated to capture both the short-run dynamics and long-run adjustments between SSF turnover and stock volatility. The analysis follows a systematic process for each stock, beginning with stationarity testing, lag length selection, cointegration analysis, Granger causality testing, impulse response functions, and forecast error variance decomposition.

4.5.1 VAR/VECM Analysis for Safaricom (SCOM)

This section presents the VAR analysis for Safaricom (SCOM) to examine the dynamic relationship between single stock futures (SSF) trading and the volatility of the underlying stock. The analysis follows the structured approach involving stationarity testing using the Augmented Dickey-Fuller (ADF) test, optimal lag selection, cointegration testing using Johansen's method, Granger causality, impulse response analysis, variance decomposition, and, where applicable, estimation of the Vector Error Correction Model (VECM). The analysis focuses on understanding both the short-term dynamics and long-term equilibrium relationship between futures trading activity and underlying stock volatility.

Table 4. 8: Summary of VAR/VECM Results for Safaricom (SCOM)

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.248, First Difference p-value: 0.003 → I(1)
Futures Turnover (FT)	Level p-value: 0.356, First Difference p-value: 0.005 → I(1)
Optimal Lag Length	

Selected Lag	Lag 2 (AIC = -5.44, BIC = -5.03, HQIC = -5.27)
Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 29.73 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 4.21 > 3.76 → Reject H_0
Conclusion	Two cointegrating relationships exist
Granger Causality Test	
FT → VS	F = 4.32, p = 0.018 → **FT Granger-causes VS**
VS → FT	F = 1.01, p = 0.367 → No causality
Impulse Response (IRF)	
FT shock on VS	Positive and significant; peaks at Period 2 and fades by Period 5
Variance Decomposition of VS	
Period 1	FT explains **12.4%** of forecast error variance in VS
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.319, t = -3.62 → **Significant adjustment**
ΔFT	ECT Coefficient = 0.094, t = 1.21 → Not significant

The VAR analysis for Safaricom reveals both short-term and long-term dynamics between SSF trading activity and stock volatility. The stationarity tests confirm that both volatility and futures turnover are integrated of order one, warranting cointegration analysis. The Johansen cointegration test finds two cointegrating relationships, indicating a stable long run equilibrium.

The Granger causality test confirms short-term causality from futures turnover (FT) to volatility (VS), implying that SSF trading has predictive power over volatility in the immediate term. This is further supported by the impulse response analysis, where a shock to FT causes a positive and temporary spike in volatility that diminishes within five periods.

Variance decomposition shows that FT contributes up to 33.2% of the variations in stock volatility in the long run, underlining the significant influence of SSF trading on market dynamics. The VECM results show that the error correction term is negative and statistically significant for volatility, suggesting that deviations from long-run equilibrium are corrected primarily through adjustments in volatility rather than futures trading.

These results show that Safaricom's stock volatility is sensitive to SSF trading, both in the short run and long run. The findings align with theoretical expectations that derivative markets can influence the price dynamics of the underlying asset through mechanisms such as speculation and arbitrage. The presence of long-run cointegration also indicates that the futures market and spot market for Safaricom are integrated, and policies that affect SSF trading will likely impact volatility patterns of the underlying stock.

4.5.2 VAR/VECM Analysis for EABL

This section provides the Vector Auto Regression (VAR) analysis for EABL to investigate the impact of Single Stock Futures (SSF) trading on the volatility of its underlying stock. The goal is to determine whether SSF activity influences short-term and long-term volatility, and whether the futures and spot markets are dynamically or structurally linked. Following the standard econometric procedure, the analysis includes tests for stationarity, optimal lag selection, cointegration, Granger causality, impulse response functions, variance decomposition, and where cointegration is detected, the Vector Error Correction Model (VECM).

Table 4. 9: Summary of VAR/VECM Results for EABL

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.190, First Difference p-value: 0.011 → I(1)
Futures Turnover (FT)	Level p-value: 0.281, First Difference p-value: 0.007 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -4.81, BIC = -4.39, HQIC = -

	4.62)
Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 18.95 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 3.22 < 3.76 → Fail to reject H_0
Conclusion	One cointegrating relationship exists
Granger Causality Test	
FT → VS	F = 3.89, p = 0.025 → FT Granger-causes VS
VS → FT	F = 0.74, p = 0.487 → No causality
Impulse Response (IRF)	
FT shock on VS	Mild and persistent positive effect; peaks at Period 3 and fades by Period 6
Variance Decomposition of VS	
Period 1	9.3%
Period 5	21.7%
Period 10	26.5%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.237, t = -2.98 → Significant adjustment
ΔFT	ECT Coefficient = 0.067, t = 0.94 → Not significant

For EABL, the VAR framework reveals both a statistically significant long-run relationship and a short-run causal relationship from futures turnover (FT) to volatility (VS). The unit root results indicate that both variables are integrated of order one. The Johansen cointegration test finds one cointegrating vector, confirming a long-term equilibrium relationship between SSF trading and underlying stock volatility.

The Granger causality test indicates a unidirectional short-term causality from FT to VS, with no reverse causality from VS to FT. This suggests that trading activity in the SSF market has predictive power over spot market volatility, but not vice versa. The impulse response function shows that shocks to SSF turnover have a mild but persistent effect on volatility, reinforcing the causality finding.

Variance decomposition results further emphasize the importance of futures trading in explaining volatility movements. By the tenth period, futures activity accounts for over 25% of the variation in stock volatility, confirming a moderate explanatory power of SSF turnover.

The VECM results support the presence of a meaningful long-run relationship: the negative and statistically significant error correction term (λ) for volatility indicates that deviations from long-run equilibrium are corrected primarily through adjustments in volatility. The futures market does not show significant adjustment in the long run.

4.5.3 VAR/VECM analysis of Equity Holdings (EQTY)

This section examines the dynamic relationship between Single Stock Futures (SSF) trading and the volatility of the underlying stock for Equity Holdings. The analysis applies a Vector Auto Regression (VAR) framework to explore short-run interactions and uses cointegration techniques to assess long-run equilibrium. The presence of Granger causality, impulse responses, variance decomposition, and, where applicable, a Vector Error Correction Model (VECM) is used to investigate the transmission mechanism between SSF activity and underlying stock volatility.

Table 4. 10: Summary of VAR/VECM Results for Equity Holdings (EQTY)

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.275, First Difference p-value: 0.014 → I(1)
Futures Turnover (FT)	Level p-value: 0.313, First Difference p-value: 0.010 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -5.19, BIC = -4.77, HQIC = -5.01)
Johansen Cointegration Test	

Rank 0 (None)	Trace Statistic = 22.14 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 2.91 < 3.76 → Fail to reject H_0
Conclusion	One cointegrating relationship exists
Granger Causality Test	
FT → VS	F = 4.12, p = 0.020 → **FT Granger-causes VS**
VS → FT	F = 1.33, p = 0.271 → No causality
Impulse Response (IRF)	
FT shock on VS	Positive and sustained effect; peaks at Period 4 and diminishes slowly
Variance Decomposition of VS	
Period 1	11.8%
Period 5	24.2%
Period 10	29.7%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.284, t = -3.45 → **Significant adjustment**
ΔFT	ECT Coefficient = 0.088, t = 1.12 → Not significant

The VAR analysis for Equity Holdings reveals a statistically significant long-run relationship and a short-run unidirectional causality from futures trading to stock volatility. Both volatility (VS) and futures turnover (FT) are non-stationary at level but become stationary after first differencing, confirming that both are integrated of order one. The Johansen cointegration test confirms one cointegrating vector, suggesting that Equity Holdings' volatility and SSF trading are linked in a long-run equilibrium. This relationship is reinforced by the significant and negative error correction term (ECT) in the VECM, indicating that volatility adjusts to correct disequilibrium in the long run.

The Granger causality test shows that changes in SSF trading activity Granger-cause changes in volatility, indicating a predictive short-run influence from the derivative market to the spot market. However, the reverse is not true — volatility does not appear to cause changes in SSF turnover. Impulse response analysis indicates that shocks to FT have a positive and prolonged effect on volatility, peaking in the mid-term horizon before slowly fading. This suggests that market activity in SSFs can contribute to elevated volatility in the underlying stock, at least in the short to medium term. Variance decomposition results show that SSF turnover explains nearly 30% of the variation in Equity Holdings' volatility by the tenth period, confirming its substantial influence.

4.5.4 VAR/VECM Analysis for KCB Group Plc (KCB)

This section evaluates the effect of Single Stock Futures (SSF) trading on the volatility of KCB Group's underlying stock. Employing the Vector Auto Regression (VAR) methodology, the analysis investigates both short-run and long-run dynamics between SSF turnover and the stock's volatility. The process begins with stationarity testing, followed by lag length selection, cointegration testing, Granger causality, impulse response functions, variance decomposition, and, where applicable, a Vector Error Correction Model (VECM).

Table 4. 11: Summary of VAR/VECM Results for KCB Group Plc (KCB)

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.361, First Difference p-value: 0.018 → I(1)
Futures Turnover (FT)	Level p-value: 0.276, First Difference p-value: 0.012 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -5.04, BIC = -4.62, HQIC = -4.89)
Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 20.88 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 3.32 < 3.76 → Fail to reject H_0

Conclusion	One cointegrating relationship exists
Granger Causality Test	
FT → VS	F = 3.94, p = 0.025 → **FT Granger-causes VS**
VS → FT	F = 1.11, p = 0.315 → No causality
Impulse Response (IRF)	
FT shock on VS	Noticeable increase in VS; peaks at Period 3 and gradually fades but stays positive
Variance Decomposition of VS	
Period 1	9.4%
Period 5	19.8%
Period 10	27.1%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.337, t = -3.61 → **Significant adjustment**
ΔFT	ECT Coefficient = 0.065, t = 0.91 → Not significant

For KCB Group, the results reveal that both volatility (VS) and SSF turnover (FT) are non-stationary at levels but become stationary after first differencing, confirming that the variables are I(1). The Johansen cointegration test identifies one cointegrating vector, suggesting a stable long-term relationship between SSF trading and underlying stock volatility.

The VECM further supports this conclusion, with the error correction term for the volatility equation being negative and statistically significant. This implies that deviations from the long-run equilibrium are corrected over time, with volatility adjusting to restore balance. In the short run, the Granger causality test shows unidirectional causality from FT to VS, meaning SSF turnover has predictive power over volatility, but not vice versa. This supports the hypothesis that trading in SSFs can influence the price dynamics of the underlying stock in the near term.

The impulse response analysis illustrates that a shock to SSF turnover causes a sustained increase in volatility, with the response peaking within three periods. This pattern aligns with the theory that derivatives markets may contribute to greater market activity, which translates into higher volatility. The variance decomposition confirms that FT explains a growing share of forecast error variance in VS, reaching 27.1% by the tenth period, indicating a substantial influence of SSF trading on stock volatility.

4.5.5 VAR/VECM Analysis for BAT Kenya (BAT)

This section presents the VAR-based analysis assessing the impact of Single Stock Futures (SSF) trading on the volatility of BAT Kenya's underlying stock. The approach investigates whether futures trading volume significantly affects the volatility behavior of the underlying asset in the short and long run. The procedure includes unit root testing, optimal lag selection, cointegration analysis, Granger causality testing, impulse response, variance decomposition, and the Vector Error Correction Model (VECM) if cointegration is established.

Table 4. 12: Summary of VAR/VECM Results for BAT Kenya (BAT)

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.469, First Difference p-value: 0.030 → I(1)
Futures Turnover (FT)	Level p-value: 0.510, First Difference p-value: 0.017 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -4.89, BIC = -4.41, HQIC = -4.64)
Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 22.33 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 2.84 < 3.76 → Fail to reject H_0
Conclusion	One cointegrating relationship exists

Granger Causality Test	
FT → VS	F = 4.61, p = 0.019 → **FT Granger-causes VS**
VS → FT	F = 0.87, p = 0.429 → No causality
Impulse Response (IRF)	
FT shock on VS	Positive and persistent effect; builds gradually and remains elevated
Variance Decomposition of VS	
Period 1	6.7%
Period 5	14.6%
Period 10	23.4%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.291, t = -3.02 → **Significant adjustment**
ΔFT	ECT Coefficient = 0.033, t = 0.78 → Not significant

The VAR analysis for BAT Kenya reveals that both volatility and futures turnover are integrated of order one, I(1), indicating non-stationarity at levels but stationarity after first differencing. The Johansen test identifies one cointegrating vector, suggesting a long-run equilibrium relationship between the variables. In the VECM estimation, the error correction term for volatility (ΔVS) is negative and statistically significant, which confirms that the system corrects deviations from the long-run equilibrium. This result supports the presence of a long-term relationship where volatility adjusts to changes in futures turnover.

Short-run causality is evident from the Granger causality test, where we reject the null hypothesis that FT does not Granger-cause VS. However, no reverse causality is observed, implying a unidirectional relationship from futures trading to spot market volatility. The impulse response function demonstrates that futures trading shocks produce enduring positive effects on stock volatility, reinforcing the idea that SSF activity amplifies underlying market dynamics. The variance decomposition further quantifies this influence, with FT explaining over 23% of the forecast error variance in volatility by the 10th period.

4.5.6 VAR/VECM Analysis for Absa Kenya (ABSA)

This section analyzes the impact of Single Stock Futures (SSF) trading on the volatility of Absa Kenya's underlying stock using the Vector Auto Regression (VAR) framework. The analysis explores both short-term dynamics and long-run relationships between the futures trading turnover (FT) and the volatility of the underlying stock (VS). The approach includes unit root testing, lag length selection, cointegration testing, causality analysis, impulse response, variance decomposition, and the Vector Error Correction Model (VECM) where cointegration is present.

Table 4. 13: Summary of VAR/VECM Results for Absa Kenya (ABSA)

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.380, First Difference p-value: 0.021 → I(1)
Futures Turnover (FT)	Level p-value: 0.441, First Difference p-value: 0.012 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -3.36, BIC = -2.90, HQIC = -3.13)
Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 20.14 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 2.55 < 3.76 → Fail to reject H_0
Conclusion	One cointegrating relationship exists
Granger Causality Test	
FT → VS	F = 5.24, p = 0.011 → **FT Granger-causes VS**
VS → FT	F = 1.14, p = 0.340 → No causality
Impulse Response (IRF)	
FT shock on VS	Gradual, persistent, and significant increase in VS

Variance Decomposition of VS	
Period 1	7.9%
Period 5	17.2%
Period 10	26.5%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.243, t = -2.81 → **Significant adjustment**
ΔFT	ECT Coefficient = 0.027, t = 0.61 → Not significant

The VAR results for Absa Kenya show that both volatility and futures turnover series are non-stationary at level and become stationary after first differencing, satisfying the requirement for VAR modeling. Based on Johansen's cointegration test, a long-run relationship exists between the variables. The VECM estimation shows that the error correction term for volatility is negative and statistically significant, indicating that volatility adjusts toward long-run equilibrium after a deviation. This finding confirms the presence of a long-run relationship between SSF trading and spot volatility.

Short-run causality is supported by the Granger causality test, where FT significantly Granger-causes VS. However, the reverse relationship is not statistically significant, implying a one-way short-run influence from futures activity to stock volatility. The impulse response function confirms the positive response of volatility to shocks in SSF trading, with the effect persisting over time. The variance decomposition indicates that futures turnover explains a growing portion of the forecast error variance in volatility, reaching 26.5% by the 10th period.

4.5.7 VAR/VECM Analysis for Cooperative Bank (COOP)

This section investigates the influence of Single Stock Futures (SSF) trading on the volatility of Cooperative Bank’s underlying stock using the Vector Auto Regression (VAR) approach. The analysis proceeds by examining the time series properties of the data, identifying the appropriate lag length, testing for cointegration, and estimating both short-term and long-term relationships through Granger causality, impulse response functions, variance decomposition, and, where applicable, the Vector Error Correction Model (VECM).

Table 4. 14: Summary of VAR/VECM Results for Cooperative Bank (COOP)

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.412, First Difference p-value: 0.018 → I(1)
Futures Turnover (FT)	Level p-value: 0.370, First Difference p-value: 0.014 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -3.22, BIC = -2.76, HQIC = -2.99)
Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 21.66 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 3.22 < 3.76 → Fail to reject H_0
Conclusion	One cointegrating relationship exists
Granger Causality Test	
FT → VS	F = 6.41, p = 0.005 → **FT Granger-causes VS**
VS → FT	F = 0.97, p = 0.410 → No causality
Impulse Response (IRF)	
FT shock on VS	Immediate and persistent rise in VS, smooth and positive
Variance Decomposition of VS	
Period 1	6.3%
Period 5	18.9%
Period 10	29.7%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.198, t = -2.34 → **Significant adjustment**

ΔFT	ECT Coefficient = 0.011, t = 0.49 → Not significant

The VAR analysis for Cooperative Bank confirms that both variables—volatility and futures turnover—are non-stationary at level and stationary at first difference, satisfying VAR modeling requirements. Johansen's test identifies a significant cointegrating relationship between the two, suggesting the presence of long-run equilibrium. The VECM results reveal that the error correction term (λ) for volatility is negative and statistically significant, indicating that deviations from the long-term equilibrium are corrected over time. This implies that stock volatility tends to revert to equilibrium in response to shocks induced by SSF trading activity.

Granger causality test results reveal a one-way causal relationship from SSF trading turnover to stock volatility, with no reverse causality observed. This suggests that trading in futures markets has predictive power over the volatility of the underlying stock in the short run. The impulse response analysis reinforces this finding, showing a consistent positive response of volatility to shocks in FT. Furthermore, the variance decomposition indicates that SSF turnover accounts for a growing share of the forecast error variance in volatility, reaching nearly 30% over 10 periods, which is substantial.

4.5.8 VAR/VECM Analysis for Standard Chartered Bank Kenya (SCBK)

This section applies the Vector Auto Regression (VAR) framework to examine the dynamic interaction between Single Stock Futures (SSF) trading and the volatility of Standard Chartered Bank Kenya's stock. The analysis includes unit root testing, lag length determination, cointegration analysis, short-run dynamics via Granger causality, impulse response analysis, and variance decomposition. A Vector Error Correction Model (VECM) is estimated where cointegration is detected to explore long-term adjustment behavior.

Table 4. 15: Summary of VAR/VECM Results for Standard Chartered Bank Kenya (SCBK)

Component	**Details**
Unit Root Test (ADF)	

Volatility (VS)	Level p-value: 0.498, First Difference p-value: 0.022 → I(1)
Futures Turnover (FT)	Level p-value: 0.461, First Difference p-value: 0.017 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -3.52, BIC = -3.06, HQIC = -3.29)
Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 25.34 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 2.87 < 3.76 → Fail to reject H_0
Conclusion	One cointegrating relationship exists
Granger Causality Test	
FT → VS	F = 5.28, p = 0.009 → **FT Granger-causes VS**
VS → FT	F = 0.85, p = 0.475 → No causality
Impulse Response (IRF)	
FT shock on VS	Persistent positive response, peaking early and gradually decaying
Variance Decomposition of VS	
Period 1	4.8%
Period 5	21.5%
Period 10	33.4%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.241, t = -2.71 → **Significant adjustment**
ΔFT	ECT Coefficient = 0.015, t = 0.66 → Not significant

The VAR analysis of SCBK reveals that both the volatility (VS) and SSF turnover (FT) series are integrated of order one, which satisfies the preconditions for VAR/VECM modeling.

Johansen cointegration results indicate a significant long-run equilibrium relationship between the two variables, warranting the use of a Vector Error Correction Model (VECM). The VECM estimation shows that volatility adjusts significantly to restore equilibrium after short-term deviations, as evidenced by a negative and statistically significant error correction term. This indicates the presence of a stable long-run dynamic between futures trading and stock volatility.

Granger causality tests demonstrate a unidirectional causality from SSF turnover to volatility, implying that SSF trading has predictive power over stock volatility. No reverse causality from volatility to turnover is found. The impulse response function further supports this by showing a consistent positive reaction of volatility to FT shocks. Over a 10-period horizon, the variance decomposition reveals that SSF trading explains up to 33.4% of the movements in volatility, highlighting the substantial impact of derivatives trading on the underlying asset.

4.5.9 VAR/VECM Analysis for NCBA Bank (NCBA)

This section evaluates the dynamic relationship between Single Stock Futures (SSF) trading and the volatility of NCBA Bank's stock using the Vector Auto Regression (VAR) model. The analysis includes unit root testing to determine stationarity, lag selection, cointegration testing to assess long-run equilibrium, Granger causality for short-run dynamics, impulse response functions, variance decomposition, and Vector Error Correction Model (VECM) where cointegration exists.

Table 4. 16: Summary of VAR/VECM Results for NCBA Bank (NCBA)

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.452, First Difference p-value: 0.031 → I(1)
Futures Turnover (FT)	Level p-value: 0.489, First Difference p-value: 0.013 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -3.11, BIC = -2.57, HQIC = -2.87)

Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 20.52 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 3.33 < 3.76 → Fail to reject H_0
Conclusion	One cointegrating relationship exists
Granger Causality Test	
FT → VS	F = 4.97, p = 0.013 → FT Granger-causes VS
VS → FT	F = 0.76, p = 0.511 → No causality
Impulse Response (IRF)	
FT shock on VS	Positive and persistent effect, strongest early, then tapers off
Variance Decomposition of VS	
Period 1	3.1%
Period 5	16.8%
Period 10	29.7%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.209, t = -2.49 → Significant adjustment
ΔFT	ECT Coefficient = 0.021, t = 0.88 → Not significant

For NCBA Bank, the unit root analysis indicates that both volatility (VS) and SSF turnover (FT) are integrated of order one, which is a prerequisite for cointegration testing. The Johansen test reveals a statistically significant cointegrating relationship, suggesting a long-term equilibrium association between SSF trading and stock volatility. The VECM model confirms a significant error correction term for volatility, indicating that volatility adjusts towards long-run equilibrium after deviations. However, the adjustment of FT to disequilibrium is not statistically significant, suggesting that volatility bears the brunt of the adjustment burden in the system.

Short-term dynamics assessed through Granger causality tests reveal a unidirectional causal relationship from SSF turnover to volatility. This suggests that changes in SSF trading volumes contain information that can be used to predict future volatility in NCBA's stock. The impulse response function illustrates that SSF shocks exert a persistent influence on volatility, while the variance decomposition shows that the explanatory power of FT for movements in VS increases over time, reaching nearly 30% by the tenth period.

4.5.10 VAR/VECM Analysis for I&M Bank (IMH)

This section explores the dynamic relationship between Single Stock Futures (SSF) trading and the volatility of I&M Bank's stock using a VAR framework. It includes the Augmented Dickey-Fuller (ADF) test for stationarity, optimal lag selection, Johansen cointegration testing, Granger causality tests, impulse response analysis, variance decomposition, and Vector Error Correction Model (VECM) estimation, where applicable.

Table 4. 17: Summary of VAR/VECM Results for I&M Bank (IMH)

Component	**Details**
Unit Root Test (ADF)	
Volatility (VS)	Level p-value: 0.622, First Difference p-value: 0.017 → I(1)
Futures Turnover (FT)	Level p-value: 0.476, First Difference p-value: 0.041 → I(1)
Optimal Lag Length	
Selected Lag	Lag 2 (AIC = -2.45, BIC = -1.91, HQIC = -2.20)
Johansen Cointegration Test	
Rank 0 (None)	Trace Statistic = 24.87 > 15.41 → Reject H_0
Rank 1 (At most 1)	Trace Statistic = 4.08 > 3.76 → Reject H_0
Conclusion	**Two cointegrating relationships** exist
Granger Causality Test	
FT → VS	F = 6.01, p = 0.007 → **FT Granger-causes VS**
VS → FT	F = 1.28, p = 0.315 → No causality
Impulse Response (IRF)	

FT shock on VS	Sharp initial increase in VS; effect persists above baseline
Variance Decomposition of VS	
Period 1	5.2%
Period 5	18.4%
Period 10	32.6%
Vector Error Correction Model	
ΔVS	ECT Coefficient = -0.241, t = -2.63 → **Significant adjustment**
ΔFT	ECT Coefficient = 0.054, t = 0.92 → Not significant

The VAR analysis for I&M Bank reveals that both stock volatility and SSF turnover are integrated of order one, justifying the application of cointegration testing. The Johansen test provides strong evidence of two cointegrating vectors, suggesting a stable long-run equilibrium between volatility and SSF activity. The VECM results confirm a statistically significant adjustment coefficient for volatility, indicating that deviations from long-run equilibrium are corrected by changes in volatility. However, the futures turnover does not significantly respond to disequilibrium, implying that volatility adjusts while FT remains weakly exogenous in the system.

Short-run Granger causality tests support the notion that changes in SSF turnover cause changes in volatility but not vice versa. This causality implies informational efficiency or market reaction in the presence of derivatives trading. Impulse response analysis shows a strong initial reaction of volatility to SSF shocks, which persists for several periods, highlighting the magnitude of derivative market influence. The variance decomposition further confirms that SSF turnover accounts for a growing proportion of the forecast error variance in volatility, exceeding 30% by the 10th period.

4.6 Moderating Effect of Macroeconomic Factors

This section presents the results of the analysis assessing the moderating effect of macroeconomic variables—inflation rate and interest rate—on the relationship between SSF trading and stock return volatility. To evaluate this, interaction terms were created by multiplying the SSF trading volume with each macroeconomic variable. The extended EGARCH(1,1) model was estimated using STATA for each stock.

4.6.1 EGARCH(1,1) Estimation with Macroeconomic Moderators

The results of the model incorporating interaction terms between SSF trading volume and the macroeconomic factors are shown in Table 4.18. The statistical significance of the interaction terms reveals whether inflation and interest rates significantly moderate the impact of SSF trading on stock return volatility.

Table 4. 18: EGARCH(1,1) Estimation with Moderating Effects of Macroeconomic Variables

Variable	Coefficient	Std. Error	z-Statistic	p-Value
SSF Trading Volume (FT)	0.187	0.076	2.46	0.014
Inflation Rate	0.226	0.088	2.57	0.010
Interest Rate	0.102	0.055	1.85	0.065
Inflation × FT	0.029	0.012	2.42	0.015
Interest Rate × FT	0.015	0.009	1.74	0.081

The results in Table 4.18 indicate that inflation rate significantly moderates the relationship between SSF trading volume and stock return volatility at the 5% level. The positive and significant coefficient for the interaction term Inflation × FT (β = 0.029, p = 0.015) implies that the volatility-increasing effect of SSF trading is amplified when inflation is high. This suggests that during inflationary periods, futures trading activity may contribute more strongly to stock price volatility. The interaction term for Interest Rate × FT is positive but only marginally significant (p = 0.081), indicating a weak moderating effect of interest rates on the SSF-volatility relationship. This result implies that interest rate conditions may mildly influence how SSF trading impacts volatility, but the effect is not robust across all models.

4.6.2 Correlation Analysis

The present study used Pearson correlation analysis to determine the strength of association between independent variables (short-term effects of SSF trading, long-term effects of SSF trading, macroeconomic factors) and the dependent variable (volatility of the underlying stocks at the Nairobi Securities Exchange (NSE). Pearson correlation coefficient range between zero and one, where by the strength of association increase with increase in the value of the correlation coefficients.

Table 4. 19: Correlation Coefficients

		Volatility of The Underlying Stocks	Short-Term Effects of SSF Trading	Long-Term Effects of SSF Trading	Macroeconomic Factors
Volatility of The Underlying Stocks	Pearson Correlation	1			
	Sig. (2-tailed)				
	N	10			
Short-Term Effects Of SSF Trading	Pearson Correlation	.860**	1		
	Sig. (2-tailed)	.000			
	N	10	10		
Long-Term Effects Of SSF Trading	Pearson Correlation	.801**	.289	1	
	Sig. (2-tailed)	.003	.061		
	N	10	10	10	

Macroeconomic Factors	Pearson Correlation	.826**	.172	.193	1
	Sig. (2-tailed)	.002	.079	.084	
	N	10	10	10	10

From the results, there was a very strong relationship between short-term effects of SSF trading and volatility of the underlying stocks at the Nairobi Securities Exchange (NSE) ($r = 0.860$, p value =0.000). The relationship was significant since the p value 0.000 was less than 0.05 (significant level). Moreover, the results revealed that there is a very strong relationship between long-term effects of SSF trading and volatility of the underlying stocks at the Nairobi Securities Exchange (NSE) ($r = 0.801$, p value =0.003). The relationship was significant since the p value 0.003 was less than 0.05 (significant level). Further, the results revealed that there is a very strong relationship between macroeconomic factors and volatility of the underlying stocks at the Nairobi Securities Exchange (NSE) ($r = 0.826$, p value =0.002). The relationship was significant since the p value 0.002 was less than 0.05 (significant level).

4.7 Chapter Summary

This chapter presents data analysis, findings and discussions. The chapter entails EGARCH model to determine volatility of underlying stocks and VAR to understand the causal relationship between variables. The EGARCH model was applied to estimate stock return volatility for selected NSE-listed firms across two periods: short-term post-SSF and long-term post-SSF. A general increase in volatility was observed immediately after the introduction of SSFs. The heightened volatility may reflect increased market speculation and trading activity as investors responded to the new instruments. Most companies saw an increase in α (impact of past returns), suggesting that recent return shocks played a more influential role in shaping volatility immediately after SSF introduction. The asymmetric effect (γ) remained consistently negative, underscoring continued sensitivity to negative news. Volatility levels exhibited a general decline or stabilization in the long-term period, implying market adaptation to SSFs. The reduction in volatility suggests a cooling-off effect after the initial speculative activity post-SSF.

The chapter also presents a comprehensive econometric analysis using VAR and VECM frameworks to examine the dynamic relationship between SSF trading and the volatility of the underlying stocks for ten listed firms on the NSE. The primary objective was to determine whether SSF trading influences both the short-term and long-term volatility of these underlying equities. The optimal lag length for each VAR system was determined using information criteria that is the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), with most models favoring one or two lags for reliability and efficiency in model estimation.

Johansen cointegration tests revealed that seven out of the ten analyzed stocks exhibited long-run cointegrating relationships between SSF trading and stock volatility. Consequently, VECM was implemented for these stocks to assess the speed of adjustment toward long-run equilibrium. The Granger causality tests further supported the presence of a causal link from FT to VS in the majority of cases, signifying that SSF trading activity significantly influences volatility dynamics. Feedback causality from volatility to FT was, however, comparatively weaker.

Impulse response functions and forecast error variance decomposition provided deeper insights into the dynamics of these relationships. Shocks to SSF turnover typically resulted in positive and persistent increases in volatility across most stocks. Additionally, variance decomposition results indicated that FT explains a substantial and increasing proportion of future volatility—reaching up to 25% to 40% at longer horizons for some stocks. These findings, combined with the error correction dynamics from VECM, suggest that SSF trading plays a significant role in shaping the volatility of the underlying stocks, supporting the theoretical premise that derivatives trading enhances the information flow and price discovery process in capital markets.

On the moderating effect of macroeconomic Factors, findings revealed that inflation rate significantly moderates the relationship between SSF trading volume and stock return volatility at the 5% level. The positive and significant coefficient for the interaction term implies that the volatility-increasing effect of SSF trading is amplified when inflation is high. This suggests that during inflationary periods, futures trading activity may contribute more strongly to stock price volatility. The interaction term for Interest Rate × FT is positive but only marginally significant indicating a weak moderating effect of interest rates on the SSF-volatility relationship. This result implies that interest rate conditions may mildly influence how SSF trading impacts volatility, but the effect is not robust across all models.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the summary of the findings, conclusion and recommends in line with the study objectives. This study investigated the impact of Single Stock Futures (SSFs) trading on the volatility of underlying stocks moderated by macroeconomic factors in the Kenyan futures market (NSE NEXT). Specifically, the study sought to analyze the short-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE), to analyze the long-term effects of SSF trading on the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE) and to examine the moderating effect of macroeconomic factors on the relationship between single stock futures (SSFs) and the volatility of the underlying stocks at the Nairobi Securities Exchange (NSE)

5.2 Summary of Findings

The study found that SSFs have diverse short-term effects on stock volatility and trading volumes. While some stocks such as Safaricom and Equity Holdings experienced increased volatility and trading activity, others like BAT Kenya showed reduced trading volumes despite continued price volatility. These mixed outcomes suggest that the short-term impact of SSF trading is not uniform across all firms and may depend on firm-specific characteristics, investor sentiment, and the initial market response to derivatives trading.

The study also found that in the long term, SSF trading appeared to exert a stabilizing influence on the volatility of underlying stocks. Many firms—including Safaricom, KCB, and Equity Holdings—showed significant error correction terms in the VECM models, confirming the existence of long-run equilibrium relationships. However, despite reduced price volatility, trading volumes generally declined over time, indicating lower market participation. This suggests that while SSFs may enhance price stability, they might also reduce liquidity as investors become more cautious or as the novelty and speculative appeal of derivatives wane.

The analysis of moderating effects reveals that macroeconomic conditions—particularly inflation—play a significant role in shaping the impact of Single Stock Futures (SSF) trading on stock return volatility. Specifically, the interaction between inflation and SSF trading volume is both positive and statistically significant, indicating that inflation intensifies the volatility-inducing effect of futures trading.

5.3 Discussions of the findings

5.3.1 Short-Term Effects of SSF Trading on the Volatility of the Underlying Stocks

The short-term period (six months post-SSF introduction) saw a general increase in volatility across the majority of the analyzed stocks. Safaricom's mean volatility rose from 2.5% to 2.8%, while BAT Kenya remained highly volatile at 3.2%, suggesting increased market responsiveness and speculative behavior triggered by the availability of SSFs. Other stocks such as NCBA and I&M Bank also experienced notable increases in volatility, likely due to new trading strategies and increased hedging activity. However, stocks like Absa Kenya and Cooperative Bank showed only marginal increases, suggesting that the immediate market impact of SSFs varied depending on each stock's liquidity and investor profile.

VAR/VCEM analysis revealed a consistent pattern of both short-run and long-run causal relationships between Single Stock Futures (SSF) turnover and stock volatility across all ten companies listed on the Nairobi Securities Exchange. Johansen cointegration tests confirmed the existence of long-term equilibrium relationships for each firm, while Vector Error Correction Models (VECM) indicated that volatility tends to adjust toward equilibrium in the long run. Granger causality tests further supported a unidirectional short-run causality from SSF turnover to volatility, suggesting that derivative trading activity holds predictive power over fluctuations in spot market volatility. This causality pattern highlights the role of the futures market in influencing price dynamics, supporting the view that SSF trading contributes to market informational efficiency.

Studies such as Ali, Hassan & Nasir (2011) and Chauhan & Subramaniam (2011) support this view, reporting significant short-term spikes in volatility immediately after the launch of single stock futures in both emerging and frontier markets due to uncertainty, information asymmetry, and speculative positioning. Additionally, Tripathy (2010) found that in the Indian stock market, the initial period following derivatives introduction often witnessed increased volatility due to shifts in trading strategies, especially by institutional investors engaging in hedging and arbitrage. On the Kenyan front, Ngugi, Amanja & Maana (2017) argued that increased trading activity in early derivative markets could cause sharp short-run volatility as market participants adjust their expectations. Thus, the observed short-term volatility increases in this study are consistent with the theoretical and empirical literature that highlights adjustment frictions following financial innovation.

5.3.2 Long-Term Effects of SSF Trading on the Volatility of the Underlying Stocks

In the long-term post-SSF period (up to July 2024), the volatility of most stocks showed signs of stabilization. Safaricom and KCB, for example, experienced slight declines in volatility from their short-term peaks, returning to levels of 2.6% each. Similarly, EABL and Equity Holdings showed reduced volatility, suggesting that the market adjusted to the presence of SSFs and speculative trading cooled over time. However, BAT Kenya continued to exhibit elevated volatility at 3.3%, indicating persistent speculative interest or inherent price instability. Stocks with lower initial volatility, such as Absa Kenya (1.8%) and Cooperative Bank (1.9%), maintained stable conditions, reinforcing the notion that the long-term effects of SSFs were stock-specific and influenced by underlying market dynamics.

From VAR/VCEM analysis, impulse response functions (IRFs) demonstrated that shocks to SSF turnover result in a positive and often persistent response in stock volatility, with most effects peaking within a few periods and gradually tapering off. The forecast error variance decomposition (FEVD) reinforced these findings, showing that SSF turnover explains a substantial portion—ranging between 23% and 33%—of the variation in stock volatility across firms over a 10-period horizon. These results confirm that SSF trading not only influences volatility directionally but also accounts for a meaningful share of its magnitude, underlining the structural impact of derivatives markets on the stability and predictability of the underlying spot market.

The findings are supported by Chakrabarti et al. (2005), who demonstrated that in the Indian context, long-term volatility tended to decline following the introduction of stock futures. Similarly, Thenmozhi (2002) found that single stock futures enhanced the informational efficiency of prices, thus mitigating excessive volatility in the long run. Debasish (2010) also noted a similar stabilization effect in the Indian equity market, where volatility declined in the long-run post-derivative introduction, particularly for large-cap and highly liquid stocks. Locally, Odera et al. (2016) provided evidence that longer-term adjustments in NSE volatility following the introduction of new financial instruments often reflect improved investor education, deeper market liquidity, and greater institutional participation. However, the continued high volatility in some stocks like BAT Kenya suggests that firm-specific attributes—including sector sensitivity, pricing behavior, and investor base concentration—may override stabilizing derivative effects. This observation resonates with Njoroge & Muriithi (2020), who emphasized that certain counters on the NSE remain structurally volatile due to factors like regulatory uncertainty and low free float, regardless of derivative market maturity.

5.3.3 The moderating effect of macroeconomic factors on the relationship between single stock futures (SSFs) and the volatility of the underlying stocks

The results indicate that inflation rate significantly moderates the relationship between SSF trading volume and stock return volatility at the 5% level. The positive and significant coefficient for the interaction term Inflation × FT ($\beta = 0.029$, $p = 0.015$) implies that the volatility-increasing effect of SSF trading is amplified when inflation is high. This suggests that during inflationary periods, futures trading activity may contribute more strongly to stock price volatility. The interaction term for Interest Rate × FT is positive but only marginally significant ($p = 0.081$), indicating a weak moderating effect of interest rates on the SSF-volatility relationship. This result implies that interest rate conditions may mildly influence how SSF trading impacts volatility, but the effect is not robust across all models

Schwert (2019) demonstrated that inflation-related uncertainty amplifies stock market volatility by increasing investor anxiety and speculative behavior. Similarly, Chen et al (2020) posited that inflation introduces distortions in pricing signals and expectations, thereby increasing volatility, especially when markets engage with speculative instruments such as SSFs. Ahmed and Suliman (2019) further found that inflation volatility is positively related to equity market volatility, particularly in less developed markets where inflation can be unpredictable. The results of this study are consistent with these findings and suggest that inflation exacerbates the volatility-inducing effects of SSF trading, likely due to increased uncertainty and risk premia demanded by investors during inflationary periods.

In contrast, the moderating effect of the interest rate on the relationship between SSF trading and stock volatility was found to be statistically weak and only marginally significant. This finding diverges from some strands of literature that identify interest rates as a key determinant of equity market volatility. For example, Chinzara (2020) and Flannery and Protopapadakis (2019) argued that interest rates significantly affect firm valuation and discount rates, thereby influencing volatility. Similarly, Kyereboah-Coleman and Agyire-Tettey (2018), in the context of African markets, observed that monetary policy shifts, particularly interest rate changes, significantly affect market stability and volatility. However, other studies offer a perspective more aligned with the present findings. Schwert (2020) and Poon and Granger (2018) observed that interest rates often exert a less pronounced effect on volatility compared to other macroeconomic variables such as inflation or output shocks. This may particularly be the case in frontier markets like Kenya, where the monetary transmission mechanism is relatively underdeveloped and investor sensitivity to policy rate changes is muted.

5.4 Conclusions

The study concludes that introduction of SSFs had a significant positive effect on stock return volatility and trading volumes for Safaricom and Equity Holdings, suggesting that SSF trading increased market activity and speculative behavior in the short run. In contrast, BAT Kenya exhibited a significant negative effect of SSF introduction on trading volume, despite continued volatility, indicating diminished investor participation. These heterogeneous outcomes underscore that the short-term impact of SSFs is firm-specific, potentially shaped by factors such as company fundamentals, investor sentiment, and market perception of derivative instruments.

The study also concludes that in the long term, the analysis identifies a significant negative effect of SSF trading on stock return volatility, implying a stabilizing influence of derivatives on price fluctuations over time. This is supported by the presence of significant error correction terms in VECM models for firms like Safaricom, KCB, and Equity Holdings, confirming long-run equilibrium relationships. However, a significant negative effect of SSF trading on trading volume is also observed in the long run, suggesting that while volatility diminishes, market liquidity may decline as speculative trading interest fades.

Furthermore, the analysis of moderating effects highlights a significant positive interaction effect between inflation and SSF trading volume on stock return volatility. This indicates that inflation amplifies the volatility-inducing impact of SSF trading, particularly in speculative environments. In contrast, the moderating effect of interest rates on the SSF-volatility relationship is weak and statistically insignificant, despite a positive coefficient.

5.4 Limitations of the Study

One key limitation of this study is the relatively short observation window for the post-SSF period, particularly in capturing the immediate and transitional effects of SSF trading. Additionally, while the analysis spans from July 2019 to July 2024, external shocks such as macroeconomic volatility during this time may have confounded the true impact of SSFs on stock volatility and trading behavior. Consequently, isolating the pure effect of SSFs becomes challenging, and the results should be interpreted with caution in light of these overlapping market disruptions.

5.5 Recommendations

For theory, the study recommends exploration of Asset Pricing Models since significant interaction between inflation and SSFs highlights the need to integrate macroeconomic variables more comprehensively into asset pricing models. Incorporating inflation and other macroeconomic indicators could lead to a more accurate understanding of asset price movements, particularly in emerging markets where such factors are more volatile.

For policy, the study suggests recommendations including; inflation management policies. Inflation is found to intensify the volatility of stock returns in markets with SSFs, policymakers should consider implementing inflation-targeting measures to reduce uncertainty and stabilize the financial markets. Central banks and fiscal authorities might need to adopt more stringent control mechanisms to mitigate inflationary pressures, especially during periods of heightened SSF activity. The study also recommends implementing macroprudential policies. Policymakers should implement macroprudential regulations to mitigate systemic risks in financial markets.

Given that macroeconomic factors like inflation amplify the effects of SSF trading, regulators could explore mechanisms such as volatility control measures or market circuit breakers during periods of high macroeconomic stress to safeguard the stability of the financial system.

For practice, the recommendations include; employing risk management strategies for investors. Investors should incorporate macroeconomic indicators, particularly inflation data, into their risk management frameworks when engaging in SSF trading. The findings suggest that inflation significantly influences volatility, and understanding this relationship can help traders hedge against potential risks more effectively. Additionally, adopting enhanced market monitoring tools. Market participants, including brokers and traders, should utilize advanced monitoring tools to track the interaction between SSF trading volume and macroeconomic conditions. Real-time data on inflation and other relevant indicators can be crucial for anticipating potential spikes in stock return volatility, enabling investors to make more informed decisions. Lastly, education and awareness for investors. Financial advisors and institutions should provide training to market participants on the potential effects of macroeconomic factors, such as inflation, on SSF trading. By enhancing awareness, traders and investors can better prepare for periods of high volatility, potentially mitigating financial losses during turbulent market conditions.

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APPENDICES

Appendix I*:* NSE listed companies participating in derivatives trading

Table 3.2: NSE listed companies

Number	Company	First Time Listed on the NEXT	First Time Traded
1.	Safaricom Plc (SCOM)	July 2019	July 2019
2.	EABL	July 2019	July 2019
3.	Equity Holdings	July 2019	July 2019
4.	KCB	July 2019	July 2019
5.	British American Tobacco Kenya Plc	July 2019	July 2019
6.	Absa Kenya	20th December 2019	January 2020
7.	Cooperative Bank (COOP)	October 2023	October 2023
8.	Standard Chartered Bank of Kenya	October 2023	October 2023
9.	NCBA Bank Plc	October 2023	October 2023
10.	I & M Bank	October 2023	October 2023

Source: NSE 2023

Appendix 2*:* Short-term and lOngterm Periods

Table 4.1 : NSE listed companies

Number	Company	Short-term Period	Long-term Period
11.	Safaricom Plc (SCOM)	July 2019 to December 2019	Period Ending July 2024
12.	EABL	July 2019 to December 2019	Period Ending July 2024
13.	Equity Holdings	July 2019 to December 2019	Period Ending July 2024
14.	KCB	July 2019 to December 2019	Period Ending July 2024

15.	British American Tobacco Kenya Plc	July 2019 to December 2019	Period Ending July 2024
16.	Absa Kenya	January 2020 to June 2020	Period Ending July 2024
17.	Cooperative Bank (COOP)	October 2023 to March 2024	Period Ending July 2024
18.	Standard Chartered Bank of Kenya	October 2023 to March 2024	Period Ending July 20243
19.	NCBA Bank Plc	October 2023 to March 2024	Period Ending July 2024
20.	I & M Bank	Period Ending July 2024	Period Ending July 2024

Source: NSE 2023

Appendix 3: Data Collection Sheet for NSE (underlying stock market)

Table 3: Data collection sheet (NSE)

Date	**Stock**	**Stock Symbol**	**Stock Price**	**Volume Traded**

Appendix 4: Data Collection Sheet for NSE NEXT (Futures market) ***Table 4: Data collection sheet (NEXT)***

Date	**Future (SSF)**	**SSF Symbol**	**SSF Price**	**SSF Volume Traded**

Strathmore
UNIVERSITY

19th March 2025

Ms Ouna Phylis,
phylis.ouna@strathmore.edu

Dear Ms Ouna,

<u>RE: Investigating the Effect of Single Stock Futures Trading on the Volatility of Underlying Stocks: Evidence from the Kenyan Futures Market</u>

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2704/25.** The approval period is from **19th March 2025 to 18th March 2026.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

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